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INFORMATION SHARING AND COLLABORATIVE FORECASTING IN RETAIL SUPPLY CHAINS

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ABSTRACT

Demand distortion, also known as the bullwhip effect, is an important problem encountered in a wide range of supply chains. To counteract this problem, it has been recommended that downstream sales data be shared with upstream members of supply chains. Furthermore, it has been suggested that even greater benefits would be attained through the implementation of collaborative forecasting in supply chains. In practice, however, many companies have found it difficult to realize the suggested benefits of information sharing and the adoption rate of collaborative forecasting remains low.

This thesis examines the benefits and challenges of information sharing and collaborative forecasting in retail supply chains. It consists of six individual studies: two simulation studies and one case study examining the value of manufacturer access to downstream sales data; one case study on collaborative forecasting; and two case studies comparing company experiences of information sharing and collaborative forecasting. The research context is the relationship between grocery retailers and consumer goods manufacturers.

Three research questions are addressed:

1. In what situations does sharing of downstream sales data with upstream supply chain members enable increased efficiency?
2. What are the prerequisites for upstream supply chain members to be able to benefit from access to downstream sales data?
3. What additional benefits and costs are associated with moving from sharing of downstream sales data to collaborative forecasting in supply chains?

In relation to Question 1 it is discovered that access to different types of downstream sales data, e.g. point-of-sale data or customer sell-through data, has different value depending on whether the aim is to reduce demand variability amplification or delay in conveying a change in demand. In addition, it is found that the replenishment frequency between the echelons of a supply chain has an important impact on the value of information sharing.

In relation to Question 2 it is shown that the manufacturer's production, planning, and purchasing frequencies limit the attainable benefits of information-sharing efforts. In addition, it is found that the manufacturer's forecasting process and level of internal integration may present obstacles to the effective use of downstream sales data. Moreover, it is demonstrated that the fashion in which downstream sales data is used in production and inventory control has an important impact on the resulting benefits.

Finally, in relation to Question 3 it is discovered that many grocery retailers currently lack the forecasting capabilities required for effective forecasting collaboration. Investing in acquiring these capabilities for the sole purpose of enabling collaboration is, in light of the attainable benefits, not feasible. However, the results of the research indicate that a great deal of the benefits of collaborative forecasting can be attained by synchronizing planning activities and by sharing more accurate sales data in the supply chain.

Keywords: bullwhip effect, collaborative forecasting, collaborative planning forecasting and replenishment (CPFR), information sharing, point-of-sale (POS) data, retail, supply chain management (SCM), vendor-managed inventory (VMI).

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Johanna Småros

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1 INTRODUCTION

1.1 Background

Lack of demand visibility has been identified as an important challenge for supply chain management (Chen, 1998; Lee, 2002; Lin et al., 2002). Commonly, the only demand information companies have access to are the orders placed by their customers (Cachon and Fisher, 2000). As both practice and research have shown, order data often give a delayed and distorted picture of end customer demand and what actually happens in the market. The distortion tends to increase when moving upstream in the supply chain, i.e. when moving further away from the end customer. This phenomenon is known as the bullwhip effect (Lee et al. 1997; 1997b) and it makes demand look variable and unpredictable even when end customer demand is level (Forrester, 1961). Controlling production and inventories based on this flawed demand information leads to inefficiencies, such as low capacity utilization, poor availability, and high stock levels (Lee et al. 1997b; Towill et al., 1992).

To remedy this problem, it has been recommended that data on end customer sales be shared within supply chains (Lee et al, 1997a; 1997b; Mason-Jones and Towill, 1997). In addition, there are studies suggesting that even greater benefits would be attained by further tightening inter-company integration through implementation of collaborative forecasting in supply chains (Lee et al., 1997b; Aviv, 2002).

However, despite the suggested benefits and examples of successful implementation (see the section on Wal-Mart below), many companies have found it difficult to realize the benefits of information sharing in practice (Cooke, 1998; Lapide, 2001; Vergin and Barr, 1999). In addition, the adoption rate of collaborative forecasting has been slower than expected (Barratt, 2004; Corsten, 2003; Sliwa, 2002). It can, thus, be concluded that there is a need for additional research examining the feasibility and value of information sharing and collaborative forecasting in supply chains.

1.1.1 The Wal-Mart example

The term vendor-managed inventory (VMI) refers to an arrangement where a vendor monitors its customer's inventory and takes responsibility for the timing of replenishment shipments. VMI offers the vendor access to information on its customer's warehouse withdrawals, i.e. its sell-through data, rather than its orders. This means that one level of order batching is removed, allowing for more accurate, more rapidly available, and more level demand information. In addition, since the vendor is free to choose the timing of the replenishment shipments, it can further dampen demand peaks, for example by delaying non-critical replenishments. (Kaipia et al., 2002).

Wal-Mart and Procter & Gamble were among the first companies to implement VMI (Cooke, 1998). This relationship gave impulse to the diffusion of VMI within the grocery sector at a pace quicker than has been observed in other sectors (Peck, 1998). However, in many situations Wal-Mart took VMI a step further than other companies. By the late 1980's, select key suppliers, including companies such as Wrangler and GE, were using VMI systems to replenish stocks in Wal-Mart's stores and warehouses. Wal-Mart transmitted sales data to Wrangler daily, which Wrangler used to generate orders for various quantities, sizes, and colors of jeans and to plan deliveries from specific warehouses to specific stores. Similarly, Wal-Mart sent daily reports of warehouse inventory status to GE Lighting, which GE used to plan inventory levels, generate purchase orders, and to ship exactly what was needed when it was needed. As a result, Wal-Mart and its vendors benefited from reduced inventory costs and increased sales. (Bradley and Ghemawat, 2002)

Beginning in 1990, Wal-Mart introduced its Retail Link system to further support information sharing in its supply chain (Bradley and Ghemawat, 2002). Originally more than 2000 suppliers and currently more than 4000 suppliers use the web-based Retail Link system to access Wal-Mart's point-of-sale (POS) data, i.e. sales data collected by store cash registers, which is updated almost in real-time. The suppliers use this data to analyze the sales trends and inventory positions of their products on a store-by-store basis. (Aviv, 2002; Bradley and Ghemawat, 2002).

Wal-Mart can also be considered a pioneer in collaborative forecasting. The first Collaborative Forecasting, Planning and Replenishment (CPFR) project was initiated in the mid 1990's by Wal-Mart and Warner-Lambert and supported by SAP, Manugistics, and Benchmarking Partners. The project was called Collaborative Forecasting and Replenishment (CFAR). During the CFAR pilot, Wal-Mart and Warner-Lambert independently estimated demand six months in advance and compared forecasts and resolved discrepancies on a weekly basis. In addition, Wal-Mart began placing its orders for the pilot product group, Listerine mouthwash products, six weeks in advance in order to match Warner-Lambert's six-week manufacturing lead-time. This made it possible for Warner-Lambert to manufacture Listerine according to consumer demand and to follow a smoother production plan. Wal-Mart, on the other hand, saw an improvement in in-stock position from 85% to 98% as well as significantly increased sales in combination with a substantial reduction in inventory. (Seifert, 2002).

During the pilot, the Voluntary Interindustry Commerce Standards (VICS) association's Working Group overseeing the project worked on developing a widely applicable model for collaborative forecasting. This later evolved into the current CPFR model, which contains the following nine steps (VICS, 1998):

1. Develop front-end agreement: The parties involved establish the guidelines and rules for the collaborative relationship.
2. Create joint business plan: The parties involved create a business plan that takes into account their individual corporate strategies and defined category roles, objectives and tactics.
3. Create sales forecast: Retailer POS data, causal information and information on planned events are used by one party to create an initial sales forecast, this forecast is then communicated to the other party and used as a baseline for the creation of an order forecast.
4. Identify exceptions for sales forecast: Items that fall outside the sales forecast constraints set in the front-end agreement are identified.
5. Resolve / collaborate on exception items: The parties negotiate and produce an adjusted forecast.
6. Create order forecast: POS data, causal information and inventory strategies are combined to generate a specific order forecast that supports the shared sales forecasts and joint business plan.
7. Identify exceptions for order forecast: Items that fall outside the order forecast constraints set jointly by the parties involved are identified.
8. Resolve / collaborate on exception items: The parties negotiate (if necessary) to produce an adjusted order forecast.
9. Order generation: The order forecast is translated into a firm order by one of the parties involved.

1.1.2 Mixed results attained by other companies

Since the introduction of the first VMI implementations in the 1980's, many companies in different industries have adopted VMI. According to several studies, VMI should bring significant benefits to the participating companies, especially the vendors (see, for example, Holmström, 1989; Waller et al., 1999). Still, it seems that few vendors have managed to attain operational benefits from VMI. A study conducted by Vergin and Barr (1999) concluded that only two out of ten large US manufacturing companies had been able to realize improvements in their management of production and only one had achieved lower internal inventories through the implementation of VMI. Cooke (1998) and Lapide (2001) report similar findings: although some companies promote VMI, many are retreating from the concept and especially manufacturing companies are skeptical about the benefits of VMI. Cooke (1998) summarizes the situation as follows: "Officially, the acronym VMI refers to Vendor-Managed Inventory. But today, some 15 years after its introduction, the initials could also stand for Very Mixed Impact."

The implementation of collaborative forecasting has also been far from straightforward. In 2001, Barratt and Oliveira (2001) called attention to the lack of widespread adoption of collaborative forecasting despite the existence of a detailed and comprehensive process model and promising initial results from high-profile pilot implementations. A few years later, almost ten years after the creation of the CPFR process model, adoption continues to be slow and large-scale implementations are still rare (KJR Consulting, 2002; Corsten 2003).

1.2 Objectives and scope of the thesis

1.2.1 Objectives of the thesis

Although extant literature almost unanimously advocates sharing of downstream sales data and collaborative forecasting in supply chains, companies that have implemented these practices have attained rather mixed results. Based on this contradiction between theory and practice, it can be concluded that the factors affecting the feasibility and value of information sharing and collaborative forecasting are still not sufficiently well understood and that additional research is needed.

This thesis has three objectives. The first objective is to understand in which situations sharing of downstream sales data with upstream supply chain members enables increased supply chain efficiency. The underlying idea is that there may be factors related to a company's business environment or supply chain structure that have an impact on the value of information sharing. In addition, sharing of different kinds of sales data, e.g. POS data or distributor sell-through data, may be applicable to different situations.

The second objective is to identify prerequisites for upstream supply chain members to be able to benefit from access to downstream sales data. The underlying thought here is that differences in companies' processes or capabilities may explain why some companies have managed to attain significant benefits from information sharing, while others have found the results of such efforts disappointing.

Finally, the third objective is to identify the additional benefits and costs associated with further tightening integration in supply chains by moving from information sharing to collaborative forecasting. Here, the idea is that there may, in fact, be valid business reasons explaining companies' reluctance to adopt collaborative forecasting practices.

1.2.2 Scope of the thesis

The research context of this thesis is the relationship between grocery retailers and consumer goods manufacturers.

Focusing on retailers and manufacturers was a natural choice as this is the supply chain interface where many information sharing and collaboration efforts have first been developed and where most of the collaboration still takes place. In addition, as the nature of demand clearly has a great impact on the value of, for example, different information-sharing efforts, focusing on a part of the supply chain where demand can be considered independent in nature improves the internal consistency of the results of this thesis. Since operations further upstream in a supply chain typically are driven by dependent demand, i.e. demand originating in production schedules, collaboration efforts between, for example, manufacturers and their material suppliers, may need to be designed differently in order to be effective (Hellström, 2003).

The choice of focusing on the grocery supply chain was again a natural one, since many collaboration approaches, such as CPFR, originate in this industry and both grocery retailers and consumer goods manufacturers are currently very interested in collaboration. In addition, there are many examples of both successful and unsuccessful collaboration available in this industry.

Two research approaches are employed in this thesis: case research and simulation based on actual supply chain data. Since most of the previous research in the field has been conducted using analytical models or surveys (see the literature review in Section 2), the use of empirical case studies and simulation models with actual supply chain data addresses a methodological gap in the research. The research presented in this thesis consists of six individual studies, two of which are based on simulation and four of which are case studies. Some results of the studies have already previously been reported in journal articles and conference papers (see Appendix I for a list of publications).

1.2.3 Composition of the thesis

This thesis consists of eight chapters. Chapter 2 starts by reviewing the literature on demand distortion, i.e. the bullwhip effect in supply chains. Next, it focuses on two proposed remedies to the problem: sharing of downstream sales data and collaborative forecasting. Based on the literature review, the research questions for this thesis are formulated in the beginning of Chapter 3. After this, the research design and the research methods used are discussed. Chapters 4 – 6 present the six individual studies that this thesis consists of. The first three studies (Chapter 4) examine sharing of downstream sales data in supply chains. The following study (Chapter 5) looks at collaborative forecasting. The last two studies (Chapter 6) contrast information sharing and collaborative forecasting. The conclusions of this thesis are presented in Chapter 7. The findings are discussed and ideas for further research are presented in Chapter 8.

2 LITERATURE REVIEW

2.1 The bullwhip effect in supply chains

The term bullwhip effect was first used at Procter & Gamble and later made popular by Lee et al. (1997 a; b). It refers to the amplification of demand variability when moving from a downstream site to an upstream site. Although the term is rather new, the phenomenon has been observed and identified in industry for a long time. Already in the beginning of the 1960's when Jay Forrester (1961) wrote his seminal piece on industrial dynamics the problem was known.

The bullwhip effect is important because it results in increased production variability and increased need for buffer stock. Costs associated with a variable production schedule are, for example, inefficient capacity utilization, overtime, hiring and firing of labor, and high levels of stock-outs (Disney, 2001). Costs associated with buffer stock are, for example, the opportunity cost of tying up money in stock holdings rather than using it in a more efficient way, the cost of warehouse space needed to store product, the costs of managing the stock, and the risk of obsolescence and shrinkage (ibid.).

2.1.1 Measuring the bullwhip effect

Bullwhip is typically measured as follows (Fransoo and Wouters, 2000):

$$bullwhip = \frac{c_{out}}{c_{in}}, \qquad (1)$$

where c_{out} and c_{in} represent the relative standard deviation of demand measured upstream in the supply chain and downstream in the supply chain, respectively. The relative standard deviation c is defined as the standard deviation (σ) of demand (D) divided with the mean demand (μ) for a specified time interval [t, t+T]:

$$c = \frac{\sigma(D(t,t+T))}{\mu(D(t,t+T))}. \qquad (2)$$

Fransoo and Wouters (2000) point out that several different bullwhip measures can be used in a given supply chain. It can be useful to focus on orders for a specific product and a specific outlet; orders for a specific products aggregated across all outlets; orders for all products for individual outlets; or aggregated orders for all products and outlets. They further call attention to the fact that bullwhip can be measured using different levels of aggregation across time. If, for example, production planning takes place on a daily basis, measuring the demand amplification per day can be useful. However, if production planning takes place more seldom, say once a week, then it is more useful to measure bullwhip at the week-level. Finally, Fransoo and Wouters (ibid.) conclude that although bullwhip can be accurately measured, it can be very difficult to specify which proportion of the total bullwhip effect can be attributed to a specific cause.

Several authors have quantified the bullwhip effect in different supply chains. Stalk and Hout (1990) provide a description of the bullwhip effect in a clothing supply chain. This has been summarized by Towill and McCullen (1999) as shown in Figure 1.

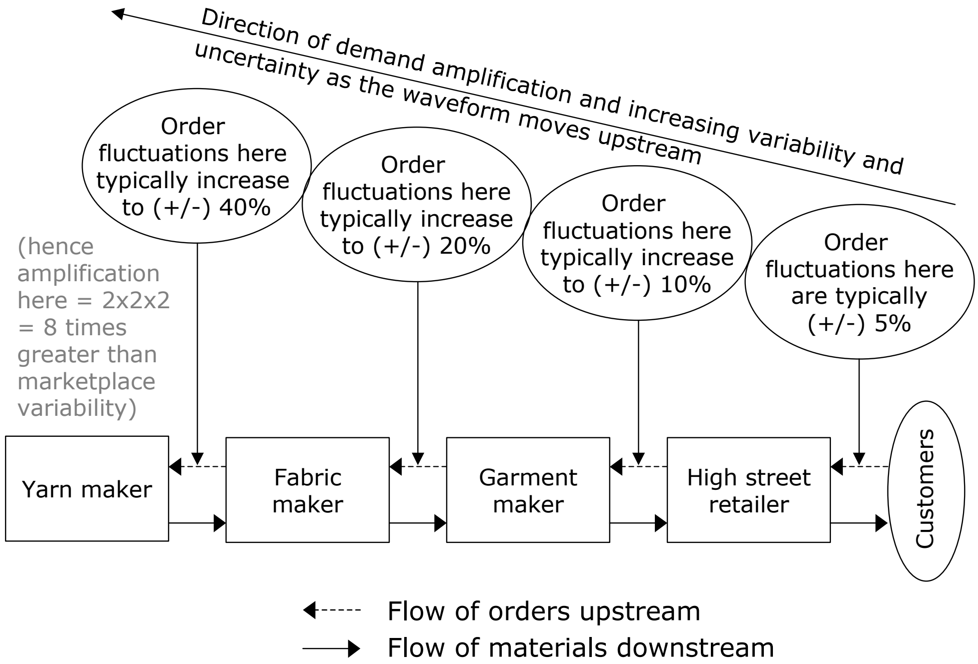

Figure 1. Bullwhip effect observed in a clothing supply chain (Towill and McCullen, 1999 based on Stalk and Hout, 1990).

Holmström (1997) describes the bullwhip effect in a confectionery supply chain. The demand variability (calculated as the standard deviation of weekly demand divided by average demand) at different echelons of the supply chain for one typical traffic-building, i.e. high volume - low margin product, and one typical profit-generating, i.e. low volume - high margin, product are presented (Table 1).

Table 1. Bullwhip effect observed in a confectionery supply chain (Holmström, 1997).

	Variability* for traffic-building product	Variability* for profit-generating product
Consumer out-take at retail outlet	10%	7%
Shop orders	26%	22%
Retail chain orders to local sales organization	75%	67%
Local sales organization's requests to European factory	54%	160%
Supply from European factory	90%	200%

*Calculated as the standard deviation of weekly demand as a percentage of average demand.

Fransoo and Wouters (2000) examine supply chains for salads and ready meals and observe notable demand amplification in both chains (Table 2). In addition, they find differences in how the individual echelons of the supply chain contribute to the bullwhip effect. They conclude that it is of great importance to distinguish the impact of each echelon separately.

Table 2. Bullwhip effect observed in supply chains for ready meals and salads (Fransoo and Wouters, 2000).

	Bullwhip effect*	
	Meals	Salads
Production	1,75	1,23
Distribution center	1,26	2,73
Retail franchisee	1,67	2,09

*Calculated using Equations 1 and 2.

2.1.2 Causes of the bullwhip effect

Lee et al. (1997 a; b) state that there are four fundamental causes of bullwhip: demand signal processing, rationing and gaming, order batching, and price variations.

Demand signal processing is essentially the same mechanism that Forrester (1961) called inventory policy. According to Forrester (ibid.), the way companies adjust inventories and in-process orders is likely to be more important to demand amplification in supply chains than any other single characteristic. He suggests that more gradual inventory corrections should be sought in order to increase the stability of the manufacturing–distribution system. Forrester (ibid.) also calls attention to the fact that many sales forecasting methods tend to accelerate inventory reactions to changes in sales levels. Lee et al. (1997a) further develop this argument by explaining how forecasts that are updated based on observed demand often lead to demand amplification. They present the following example: "Suppose, for example, that the retailer experiences a surge of demand in one period… The retailer will order a quantity to bring the inventory back to the original level… plus an additional quantity… to reflect the update of her future demands…" As a result, the demand observed at the retailer is transmitted to the supplier in an exaggerated form, and it is impossible for the supplier to distinguish which part of the order reflects an actual change in market demand and which part is caused by the retailer's inventory adjustment.

Rationing and shortage gaming, sometimes called the Houlihan effect (Disney, 2001), was identified by Houlihan (1987) who discovered that as shortages or missed deliveries occur in supply chains, customers tend to over-load their schedules or orders. This, in turn, places more demands in the production system, which leads to even more unreliable deliveries. Customers then increase their safety stock target to try to protect their business, which further distorts the demand signal, thus generating the bullwhip effect. As discussed by Lee et al. (1997 a; b) similar problems occur when customers anticipate shortages. If product allocation in a shortage situation is based on customers' orders, it may be beneficial from the customer's point of view to inflate its orders. When this happens it becomes hard to estimate true demand upstream in the supply chain, which makes decisions concerning investments in additional production capacity and raw material acquisitions very difficult. Lee et al. (1997 a; b) recommend allocation based on customers' past sales as a remedy to the gaming problem.

Order batching refers to the practice of accumulating a certain amount of demand before placing an order up the supply chain or on the manufacturing process. Batching is often the result of an economic order quantity (EOQ) calculation or similar technique. Burbidge (1989) discusses the problems that this causes in detail. Among other things, he shows how the different order cycles generated by EOQ calculations may cause large, seemingly random fluctuations in demand. In order to stabilize the order and material flow, Burbidge (ibid.) recommends moving to single-cycle flow control in production. Lee et al. (1997a; b) discuss the impact of built-in cycles in companies' processes. Many manufacturers, for example, place purchase orders with suppliers when they run their material requirements planning (MRP) systems. Since these MRP runs often take place only once a month, the result is significant batching in the supply chain. Finally Lee et al. (ibid.) highlight the importance of institutional habits, such as end-of-quarter or end-of-year surges when salespeople are trying to meet their sales targets.

Price variations refers to the practice of offering products at reduced prices to stimulate demand. This creates temporary increases in demand rates as customers take advantage of this opportunity and forward buy or stock up. However, this has serious impacts on the dynamics of the supply chain, as when the price is released from the discounted level, demand slumps, creating a perceived need for further discounting in order to stimulate demand. Lee et al. (1997 a, b) suggest reduction of price variation as a remedy to the bullwhip problem. By switching to an every-day low price (EDLP) strategy, demand can be made more level and supply more efficient, while the product and its supplier remain competitive in the eyes of the customers.

Lee et al. (1997a; b) emphasize that the bullwhip effect is the result of rational decision-making by members in the supply chain. However, Forrester (1961) and Sterman (1989) suggest that the problems are further aggravated by the decision-makers' cognitive limitations, such as the tendency to not fully account for one's supply line when making ordering decisions.

2.1.3 Means of counteracting the bullwhip effect

Several means of counteracting the bullwhip effect have been presented. Forrester (1961) suggests that the biggest benefits would be attained if companies changed their inventory control and forecasting policies. By making more gradual inventory corrections in response to changes in the market place, the stability of the supply chain could be much improved. Using simulation, he shows how a notable reduction of production variability can be achieved without increasing inventory extremes. In addition, Forrester (ibid.) proposes the elimination of supply chain echelons to reduce demand amplification. However, he declares that faster order handling would only result in a slight improvement.

Lee et al. (1997a; b) present some additional remedies (see Table 3). To reduce the batching problem, they suggest minimizing ordering costs through automation, offering discounts on assorted truckloads, using consolidation services of third party logistics provides, as well as through implementing regular delivery appointments. The main solution to the problem of varying price levels is simply to move from a promotion-oriented way of doing business to an EDLP logic, in which competitiveness is based on continuously low prices. When there is a risk of shortage and gaming, Lee et al. (1997a; b) suggest that manufacturers share capacity and supply information in order to relieve their customers' concerns. When allocation is unavoidable, they suggest that allocation schemes based on past sales rather than current orders should be used.

Finally, to tackle perhaps the most important and most prevalent cause of the bullwhip effect - demand signal processing - Lee et al. (1997a; b) emphasize the need for sharing POS data and customer sell-through data in supply chains in order to give all supply chain members access to as accurate demand information as possible. Lee et al. (1997a) state: "Sell-through data and information on inventory status at downstream nodes are keys to improving channel coordination and dampening the bullwhip effect." However, according to Lee et al. (ibid.) differences in forecasting methods will still lead to fluctuating orders and demand distortion, even when sales data is shared in the supply chain. Therefore, they suggest that it would be beneficial to have a single member of the supply chain perform forecasting and ordering for the entire supply chain.

Table 3. Causes and counter-measures of the bullwhip effect (Lee et al., 1997a).

Causes	Contributing factors	Counter-measures	State of practice
Demand signaling	▪ No visibility of end demand ▪ Multiple forecasts ▪ Long lead-time	▪ Access sell-through or point-of-sale data ▪ Single control of replenishment ▪ Lead-time reduction	▪ Sell-through data in contracts (e.g. HP, Apple, IBM) ▪ Vendor-managed inventory (P&G and Wal-Mart) ▪ Quick response manufacturing strategy
Order batching	▪ High order cost ▪ Full truckload economics ▪ Random or correlated ordering	▪ Electronic data interchange, computer assisted ordering ▪ Discount on assorted truckload, consolidation by 3rd party logistics ▪ Regular delivery appointment	▪ McKesson, Nabisco ▪ 3rd party logistics in Europe, emerging in the US ▪ P&G
Fluctuating prices	▪ High-low pricing ▪ Delivery and purchase asynchronized	▪ Every-day low price strategy ▪ Special purchase contract	▪ P&G (resisted by some retailers) ▪ Under study
Shortage gaming	▪ Proportional rationing scheme ▪ Ignorance of supply conditions ▪ Unrestricted orders and free return policy	▪ Allocate based on past sales ▪ Shared capacity and supply information ▪ Flexibility limited over time; capacity reservation	▪ Saturn, HP ▪ Scheduling sharing (HP, Motorola) ▪ HP, Sun, Seagate

Lee et al. (1997a; b) are not alone in emphasizing the importance of giving upstream supply chain members access to downstream sales data. Kiely (1998), for example, recommends that companies base their forecasts and production plans on POS data whenever possible. If POS data is not available, sell-through data provide the next best alternative. The need for forecasting collaboration in supply chains is also recognized by several authors. Barratt and Oliveira (2001) agree that sharing of sales data provides only partial visibility and maintain that forecasting collaboration can bring much greater benefits. Helms et al. (2000) also argue that forecasting collaboration is key to supply chain efficiency.

In the following sections, literature on sharing of downstream sales data with upstream members of the supply chain as well as on inter-company forecasting collaboration is reviewed and gaps in theory identified. The identified gaps lead to the research questions and the research design of this thesis as presented in Chapter 3.

2.2 Sharing of downstream sales data in supply chains

In an article published in 1996, Bourland et al. (1996) state that that the operational implications of sharing of downstream sales or inventory data with upstream members of the supply chain, or as they put it, timely demand information, have not been extensively examined. More recently, however, several researchers have made attempts to quantify the operational value of sharing of downstream sales data. The main research approach has been analytical or simulation modeling.

2.2.1 Modeling-based research

Independent and identically distributed demand

Gavirneni et al. (1999) use a model consisting of one manufacturer and one retailer facing demand that is independent and identically distributed across time. The manufacturer has limited production capacity. Two cases of information sharing between the manufacturer and the retailer are compared to the base case of only orders being transferred. In the first case, the manufacturer obtains information from the retailer about the parameters of the underlying demand distribution and the ordering policy adopted by the retailer. In the second case, the manufacturer obtains additional, immediate information on the retailer's inventory situation. Gavirneni et al. (ibid.) conclude that the benefits of information-sharing are the highest when: end-item demand variance is moderate, the fixed order cost to the retailer (i.e. the order batching done by the retailer) is moderate, and when the manufacturer has moderate to high capacity.

Similarly, Cachon and Fisher (2000) study the value of sharing of retailer inventory data using a model with one supplier, N identical retailers, and demand that is independent and identically distributed across retailers and time. In the model, the supplier uses the additional demand information to better allocate inventory among the retailers and to improve its order decisions. In a numerical study, Cachon and Fisher (ibid.) find that supply chain costs are 2,2% lower on average when the supplier has access to additional demand information. The maximum difference is 12,1%. Furthermore, they contrast the value of information sharing with a reduction in lead times and smaller batch sizes. In their numerical analyses, cutting lead times nearly in half reduces costs by 21% on average and cutting batches in half reduces costs by 22% on average, i.e. the impact is notably larger than that of information sharing.

Aviv and Federgruen (1998) examine a two-echelon supply chain consisting of a single supplier and N retailers. For each of the retailers demand is independent and identically distributed across time. Aviv and Federgruen (ibid.) contrast a traditional order-based supply chain setting with a VMI setting in which the supplier decides on the timing of replenishment shipments based on information on the retailers' sales and inventory levels. They also examine an intermediate situation in which the retailers' sales data and inventory policy information are shared but the retailers continue to be responsible for managing their own inventories. Based on a numerical study, Aviv and Federgruen (ibid.) conclude that the system-wide costs under VMI are uniformly lower than under information sharing, and this by an average of 4,7%. The average improvement due to information sharing is 2% and most of these savings are due to reductions of the supplier's costs. The benefits of both information sharing and VMI increase when supplier capacity becomes tighter or when the retailers are non-identical. Aviv and Federgruen (ibid.) further show that the benefits of information sharing and VMI are expected to be larger when demands are correlated over time and that the results of their study, due to the assumption of independent demand, present a conservative picture of the attainable benefits.

Chen (1998) considers a serial inventory system with N echelons. End-item demand is continuous, compound Poisson: customers arrive at the downstream echelon according to a Poisson process and the demand sizes of the customers are independent, identically distributed random variables. The results can be extended to discrete-time models with independent and identically distributed demands. Chen (ibid.) compares two scenarios: one that is based on echelon stock (the inventory position of the subsystem consisting of the echelon itself and all downstream echelons), and another that is based on installation stock (i.e. the local inventory position). The former requires centralized information while the latter does not. Chen (ibid.) finds that centralized information lowers supply chain costs by 0 – 9%, and on average by 1,8%. It is also found that the value of centralized information increases in the number of echelons, the lead-times, and the batch sizes.

Zhao (2002) examines a single-product, two-echelon supply chain involving a single capacitated manufacturer and single retailer facing independent demand. The manufacturer's production capacity is proportional to the time available for production. The retailer has a fixed ordering interval but shares its sales data more frequently. It is assumed that the manufacturer reviews and uses this information immediately. A computational study reveals that in a make-to-stock production system, the cost savings resulting from the information sharing increase as production capacity increases. Indeed, cost savings increase from about 3 to 35% as capacity over mean demand increases from 1.2 to 3 for various external demand distributions. This is intuitive because as capacity increases, the optimal policy would postpone production as much as possible and take advantage of all information available prior to the time production starts.

Kaipia et al. (2002) present a method for estimating the value of supplier access to customer sales data and implementation of VMI between a supplier and its customer. The unit of measure is time and the result is the time saving gained by eliminating the ordering delay, i.e. the additional time that a supplier gets to efficiently organize its operations. The time benefit is calculated by comparing two product-level data series: the order flow and the customer's sales data. Kaipia et al. (ibid.) use the method to estimate the time benefit in three cases and conclude that the value of information-sharing tends to be higher for slow-moving products, i.e. products that have large replenishment batches compared to their demand, than for fast-movers. In addition, they show that VMI is key to attaining the full benefits of information sharing.

Gamma-distributed demand

Fransoo et al. (2001) examine a situation with one supplier and N retailers facing Gamma-distributed demand. They examine the problem of designing a supply chain planning approach that keeps cooperative retailers' demand information secret from the other members of the supply web while still enabling optimization inventory levels. Fransoo et al. (ibid.) show that in the traditional context of centralizing information, the only option to keep the information private is to treat the supply chains of the cooperative and the non-cooperative retailers separately, which reduces the inventory pooling opportunities and, thus, reduces supply chain efficiency. Instead they propose a two-phased planning approach: The supply web is first split into one part containing the cooperative retailers and another part containing the non-cooperative retailers. The optimal intermediate service level for the cooperative part is determined. Next, the calculated service level as well as the service levels required by the non-cooperative retailers are used to calculate an optimum network solution. This approach is shown to result in the inventory levels at the non-cooperative retailers remaining roughly unchanged, whereas a reduction in inventory at the cooperative retailers is possible.

Autoregressive demand

The majority of the above-mentioned articles are based on demand processes that are independent and identically distributed over time. The inventory or demand information made available to the suppliers is typically used to make better inventory allocation decisions. Several researchers have, however, also used autoregressive demand processes in their models. According to Lee et al. (2000), when the underlying demand process is autoregressive, the manufacturer can use retailer demand information to derive a more accurate forecast of future orders to be placed by the retailer.

Lee et al. (2000) use an analytical model of a simple two-echelon supply chain involving one manufacturer and one retailer facing autoregressive demand. Their analyses indicate that access to information on the retailer's demand could provide significant inventory reduction and cost savings for the manufacturer. However, the underlying demand process and the lead-times have significant impact on the magnitude of the attainable benefits. Specifically, the results indicate that the manufacturer would experience great savings when: demand correlation over time is high, the demand variance within each time period is high, or lead-times are long. When the demand parameters are set so that the demand process is independent and identically distributed, there is no value of information sharing. It is important to note that although the paper assumes that the manufacturer knows the parameters associated with the retailer's demand process, which means that the manufacturer could use historical data to obtain additional information about the retailer's demand, Lee et al. (ibid.) consider this situation too complex to analyze analytically and limit the scope of their examination by assuming that the manufacturer does not use its historical order data. Yet, they admit that efficient utilization of historical order data would reduce the value of information sharing.

Later, Raghunathan (2001) has examined the model presented by Lee et al. (2000) and shown analytically and through simulation that the manufacturer's benefit is insignificant when the parameters of the utilized demand process are known to both parties. The key reason for the difference in results is that in Raghunathan's (2001) model, the manufacturer takes advantage of the entire order history to which it has access and, in this way, manages to reduce the variance of its forecast. Raghunathan (ibid.) concludes that when intelligent use of already available internal information, i.e. order history, suffices, there is no need to invest in inter-organizational systems for information sharing. Shared information is valuable only when it cannot be deduced from extant data. For example, if the retailer would share information on promotions, it would be valuable to the manufacturer. In addition, if the demand process changes over time, then the manufacturer may benefit significantly from information sharing.

Yu et al. (2001), despite Raghunathan's (2001) criticism, build on the model presented by Lee et al. (2000). They use the same two-echelon supply chain setting and the same autoregressive demand process with parameters known to the supply chain members as in Lee et al. (2000). Yu et al. (2001) compare a traditional order-based supply chain setting to a situation where the manufacturer gets access to retailer sales data and to a situation where the manufacturer controls the retailer's inventory through a VMI arrangement. The results for the first two scenarios are similar to those attained by Lee et al. (2000). In addition, Yu et al. (2000) show that VMI further increases the manufacturer's benefits.

Chen et al. (2000) examine the impact of forecasting and lead-times on the bullwhip effect. They start with a simple, two-echelon supply chain consisting of a single retailer and a single manufacturer and then extend the analysis to multiple-echelon supply chains with and without centralized customer demand information. In the scenario of centralized information, all supply chain members use the same sales data to produce the same moving-average forecast. The end-item demand process is auto-regressive. Chen et al. (ibid.) demonstrate that the bullwhip effect can be reduced, but not completely eliminated, by centralizing demand information. For supply chains with centralized information, the increase in variability at each echelon is an additive function of the lead-time and the lead time squared, while for supply chains without centralized information, the lower bound on the increase in variability at each echelon is multiplicative.

Unknown demand

Cachon and Fisher (2000) state that sharing of downstream sales data is likely to have a significantly greater value in situations of unknown demand, such as new product introductions or promotions. In situations like these, information sharing would improve the supplier's ability to detect a shift in the demand process. However, there is an apparent scarcity of research in this area.

Fisher and Raman (1996) look at how early order data can be used to improve forecast accuracy and to make better production decisions in a situation of new products being sold during a limited sales season. They present a method for estimating the demand distributions of new products, for incorporating information on early sales into the planning process, and for making production decisions before and during the season. They test the model by applying it in parallel with traditional decision-making at Sport Obermeyer and conclude that the new planning method would have resulted in a reduction in stock-out and markdown costs of 1,82%.

Mason-Jones and Towill (1997; 1999) use simulation to study the value of manufacturer access to POS data when there is a 20% step increase in demand. They examine a four-echelon supply chain involving a retailer, a distributor, a warehouse, and a factory. A traditional setting where the demand signal is transmitted through orders in the supply chain is contrasted with a situation where the supply chain members use a combination of internal sales data and POS data for inventory and production control purposes. All sales data is smoothed to lessen the impact of spikes in the market place and to avoid excessive ramping up and down of production. Mason-Jones and Towill (1999) vary the percentage of POS against order data used in decision-making and conclude that when at least 50% of the orders placed are based on POS data, demand amplification and response times are reduced. In the full-information scenario, the delay of initial response to a demand change is eradicated and production overshoot is reduced by 50% compared with the traditional supply chain setting. Mason-Jones and Towill (1997) also examine the impact of giving only part of the supply chain access to POS data. They conclude that the benefit of information sharing is much larger when all members have access to the data than when only the distributor is given access (corresponding to a VMI setting).

2.2.2 Empirical research

There is surprisingly little empirical research on the sharing of sales data in supply chains. Most of the research available focuses on replenishment collaboration, such as VMI.

Daugherty et al. (1999) examine the adoption and performance of automatic replenishment programs through a survey of US manufacturers and retailers. The results, although based on a small sample, indicate fairly widespread use or plans for future use of automatic replenishment programs in general and VMI in particular. Furthermore, the study finds a positive relationship between the effectiveness of automatic replenishment programs and company performance. The study does not, however, attempt to explain what lies behind this relationship.

Holmström (1998) presents a case study on the implementation of VMI between a vendor and a wholesaler. He states that the pilot implementation did significantly reduce demand variability for the vendor, but he does not present any evidence of an increase in the vendor's operational efficiency resulting from full implementation of VMI. However, the wholesaler's administration costs and inventory levels for the vendor's products are shown to have been reduced.

Vergin and Barr (1999) study ten Fortune 500 consumer products manufacturing companies involved in VMI. The companies produce goods sold by the grocery trade, including paper, dairy products, food products, beverages, drugs, and health-care products. Vergin and Barr (ibid.) conclude that although the manufacturers' VMI customers have benefited from improved availability and lower stock levels, only two of the manufacturing companies have been able to realize improvements in their management of production and only one has achieved lower internal inventories. Although the study does not provide any direct explanation for this observation, the authors speculate that it may be caused by the limited scale of VMI activities. For most of the examined manufacturers, VMI customers represent only about 20% of their total business.

Lapide (2001), based on his experiences from consulting projects, concludes that although VMI should support the vendor in its planning and forecasting tasks, this requires that the customer's inventory replenishment needs are tightly integrated into the vendor's operational planning processes and systems. According to Lapide (ibid.) this is seldom the case. Companies tend to focus on the transactional aspects of VMI, i.e. the execution of replenishments, billing etc. The impact on planning and forecasting, such as the use of customer sell-through rather than "sell-in" data in forecasting, is seldom included.

2.2.3 Gaps in theory

When examining the existing literature on sharing of downstream sales data with upstream members in supply chains, some important areas in need of further research can be identified.

Most of the research on information sharing to date has been conducted using analytical models with either stationary or auto-correlated demand processes. Although several authors (cf. Cachon and Fisher, 2000; Lee et al., 2000) suggest that sharing of sales data could be more valuable in situations of changing, irregular demand, very little research has focused on this particular area. Results of the simulation study conducted by Mason-Jones and Towill (1997; 1999) suggest that when there is a step change in demand, access to POS data should be very valuable to a manufacturer. Fisher and Raman (1996) also show that early sales data can be used to accurately update forecasts. However, there is clearly need for more research in this area.

Although most of the research agrees that manufacturers are to benefit the most from information-sharing efforts (cf. Raghunathan, 1999; Yu et al., 2001), many manufacturers seem to have found it difficult to realize these benefits in practice (Lapide, 2001; Vergin and Barr, 1999). The mechanisms enabling or hindering companies to benefit from access to downstream sales data are clearly not sufficiently well understood. In addition, the situational factors affecting the value of information sharing need further examination. Extant models look at different ways of making use of the sales and inventory data. In some studies, the information is used to improve forecast accuracy upstream in the supply chain (cf. Gavirneni et al., 1999; Lee et al., 2000), in others the main goal is to optimize inventory levels and inventory allocation in the supply chains (cf. Cachon and Fisher, 2000; Fransoo et al., 2001). The impact of certain supply chain characteristics, especially capacity, lead-times, demand correlation between retailers, and demand variability, is also examined (cf. Aviv and Federgruen, 1998; Chen, 1998; Gavirneni et al., 1999). However, the impact of other factors, such as product characteristics or the manufacturer's production planning process has to date been subject to very little research.

Finally, the value of different kinds of sales data, such as customer sell-through or POS data, has been subject to very little research. Yet, it is known that different types of sales data may suffer from different degrees of distortion (Fransoo and Wouters, 2000).

2.3 Collaborative forecasting in supply chains

Authors, such as Lee et al. (1997b) and Barratt and Oliveira (2001) argue that although sharing of downstream sales data is beneficial, it does not provide enough demand visibility. Instead, companies should share and collaboratively develop forecasts.

The literature on inter-company forecasting collaboration can be classified into two categories: modeling-based research, mainly published in operations research oriented academic journals, and empirical research consisting primarily of journalistic case descriptions published in trade journals and reports but also of a few more rigorous case studies and surveys reported mainly in logistics oriented academic journals.

2.3.1 Modeling-based research

Raghunathan (1999) examines the value of sharing of forecasts using a model involving a single manufacturer selling its product to two independent, identical retailers. It is assumed that the manufacturer does not face capacity constraints and that demand is stochastic and stationary, drawn from a uniform distribution. It is also assumed that the retailers' forecasts are always accurate and reliable, i.e. when shared they completely eliminate the manufacturer's uncertainty concerning the retailers' demand. Raghunathan's (ibid.) main finding is that the sharing of downstream forecasts decreases the manufacturer's costs when one or both retailers participate in the information sharing. The incremental decrease is higher when the second retailer participates. In addition, he concludes that sharing of forecasts always decreases the cost of the participant retailer. However, the cost of the non-participant retailer decreases when the manufacturer allocates potential product shortage equally between retailers, and increases when the manufacturer guarantees the order quantity for the participant. Finally, it is found that the above effects are strengthened when demand uncertainty is high. According to Raghunathan (ibid.), there are incentives for all players to move towards universal retailer participation in forecasting collaboration.

Aviv (2001) examines the value of forecasting collaboration in a two-echelon supply chain of a single product that faces independent, identically distributed demand. The members of the supply chain are a single supplier and a single retailer. Aviv (ibid.) compares a situation called collaborative forecasting, where the retailer and the supplier develop and employ a joint forecast, to a situation termed local forecasting, where each party develops and employs its own forecast. Assuming a collaboration method that results in the joint forecast always being at least as good as the best individual forecast he demonstrates that collaborative forecasting is beneficial. Based on a numerical study, Aviv (ibid.) concludes that forecasting collaboration results in an average cost reduction of 10% in the supply chain. Forecasting collaboration is also shown to be more beneficial when retailer and supplier forecasting capabilities are diversified, i.e. when they have access to different information and look at different explaining variables. It is also found that the value of collaboration increases when lead-times in the supply chain decrease.

In a more recent paper, Aviv (2002) further develops the model by introducing auto-regressive demand. Three settings are compared. In the first setting, the retailer and the supplier do not share their observations of market signals and develop and update their forecasts separately. In the second setting, resembling VMI, the supplier takes full responsibility of managing the supply chain's inventory, but the retailer's observations of market signals are not transferred to him. Forecasts are developed and updated by the supplier. In the third setting, called collaborative forecasting, inventory is managed centrally and all demand-related information is shared. A joint forecast is developed and updated based on both parties' demand information. The study shows that the value of information sharing increases when the explainable portion of demand variability increases and that the choice of the best inventory control approach - centralized inventory control or different types of decentralized inventory control - depends on whether the retailer or the supplier has more explanation power.

Zhao et al. (2002) use simulation to examine the impact of forecasting model selection on the value of information sharing in a supply chain with one capacitated supplier and four retailers. Four types of demand patterns representing different combinations of seasonality and trend are examined. In addition, five different forecasting methods – the naïve method, simple moving average, double exponential smoothing, no-trend Winter's, and three-parameter Winter's – are used, which in combination with the demand patterns produce different forecast errors. The supplier's capacity is also varied. Zhao et al. (ibid) study three different levels of information sharing: sharing of retailers' orders only, sharing of both retailers' orders and retailers' forecasted net requirements, and sharing of both retailers' orders and retailers' planned orders. They show that sharing of retailers' planned orders is more beneficial than sharing of forecasted net requirements. The more accurate the forecast, the more valuable information sharing usually is. However, retailer forecast accuracy does not have a substantial impact on supply chain performance if the information is not shared. If forecast information is indeed shared, increasing retailer forecast accuracy becomes very attractive. Information sharing is most valuable when capacity utilization is moderate or high. Most of the benefits of information sharing are shown to go to the supplier.

2.3.2 Empirical research

The majority of empirical data available on inter-company forecasting collaboration consists of journalistic case descriptions presented in the trade press. Most of these practitioner-oriented reports focus on one collaboration model, the CPFR process model sponsored by the VICS association.

In recent years, both the VICS CPFR committee and ECR Europe have published several reports presenting pilot implementations of the CPFR process model and providing recommendations and roadmaps for companies interested in implementing it (see, for example, Accenture, 2001; Accenture, 2002; VICS, 1999). These sources indicate that by implementing CPFR both retailers and suppliers can expect to benefit from increased forecast accuracy, reduced stock-outs, increased sales, and reduced inventories. Other suggested benefits include reduced delivery lead-times from suppliers to retailers and higher capacity utilization for suppliers.

Fliedner (2003) has examined several trade journals and reports and comes up with a similar list of benefits. He also presents a list of obstacles to forecasting collaboration: lack of trust in sharing sensitive information, lack of internal forecast collaboration, availability and cost of technology or expertise, aggregation concerns (number of forecasts and frequency of generation), and fear of collusion.

Stank et al. (1999) present the results of a survey assessing the levels of involvement in cross-organizational collaboration among firms utilizing automatic inventory replenishment. The results reveal moderate levels of collaborative planning, forecasting and replenishment across all firms in the sample. Higher levels of implementation are noted for joint planning/replenishment (mean score of 4.38 out of 7) than for joint forecasting (mean score of 4.08 out of 7). Stank et al. (ibid.) also explore the anticipated association between high levels of CPFR implementation and effectiveness in achieving operational performance goals. Results for high and low CPFR firms are, however, found to be significantly different on only two of nine performance goal variables; high CPFR firms perceive higher levels of achievement of performance goals related to reduced handling and cost reduction.

Based upon a review of existing literature and a survey of participants in existing CPFR implementations, Barratt and Oliveira (2001) identify inhibitors and enablers of CPFR. Their survey identifies lack of discipline to properly execute the preparatory phases of the CPFR process model, lack of joint planning, difficulties in managing the exceptions and review processes related to sales and order forecasting, and lack of shared targets as significant inhibitors. Technology and trust are identified to be the main enablers of CPFR.

Skjoett-Larsen et al. (2003) present a survey among Danish companies on supply chain management and CPFR. Their results show that companies in general have a positive attitude towards inter-company collaboration but that different companies value different areas, such as collaboration on promotions or replenishments, differently.

Simatupang and Sridhar (2005) develop instruments for measuring the level of collaboration based on three dimensions: information sharing (e.g. POS data, information on promotional events, demand forecasts, or information on price changes), synchronization of decisions (e.g. joint plans on product assortments, promotional events, or joint demand forecasts), and alignment of incentives (e.g. joint frequent shopper programs, shared savings, or delivery guarantees for peak demand). They use these instruments to analyze survey data collected from 76 companies in New Zealand and identify a positive link between collaboration and operational performance. However, they do not separate the impact of the specific collaboration practices on performance.

McCarthy and Golicic (2002) present one of the few case studies available on collaborative forecasting. They criticize the CPFR process model for being too detailed and comprehensive and examine three companies engaged in alternative kinds of forecasting collaboration with their trading partners. The sales force of one of the companies conducts monthly forecasting calls to customers to review sales forecasts. Another company first sends its customers a system-generated forecast for review and then updates it in collaboration with the customer. The third company sends its supplier a 12-week rolling forecast on a weekly basis and engages in weekly conference calls with the supplier in order to develop a collaborative forecast. Based on the cases, McCarthy and Golicic (ibid.) conclude that forecasting collaboration can be very beneficial, resulting in such improvements as increased responsiveness, improved product availability, as well as inventory and cost optimization. They recommend that companies develop collaboration practices that require less investment in human or technological resources than the CPFR process model does. They do not, however, suggest any concrete practices, they only recommend that companies establish regular meetings for discussing forecasts with their supply chain members and that they develop one shared forecast.

Barratt (2004) presents the results of case study of six organizations across three tiers of a coffee supply chain in the UK. The study involves a retailer and a manufacturer who at the time of the study were two years into a project seeking to develop collaborative planning and trying to expand it upstream in their supply chain to include packaging and raw material suppliers. The study was conducted through in-depth interviews with key informants representing the retailer, the manufacturer, and four packaging suppliers. Based on the case study, Barratt (ibid.) presents a large number of enables and inhibitors of collaborative planning. He emphasizes the need to integrate collaboration efforts with the companies' operational and strategic activities. In addition, he concludes that internal integration, i.e. integration between marketing and production functions, needs to be in place. Furthermore, extensive information sharing and process alignments are considered key.

2.3.3 Gaps in theory

When examining the existing literature on inter-company forecasting collaboration, areas in need of further research can be identified.

Modeling-based research in the area of collaborative forecasting seems to rely on some very strong assumptions. Raghunathan (1999), for example, assumes that retailers can produce perfect demand forecasts and only presents the following claim as support for this assumption: "in general, retailers know their demand better than the manufacturer." Aviv (2001; 2002) assumes that combining the retailer's and the supplier's forecasts always improves forecast quality. These assumptions have, however, not been validated through empirical research.

Another important observation is that company actions appear to be contrary to academic research. Whereas research supports collaborative forecasting as a means of improving supply chain efficiency (cf. Aviv, 2002; Zhao, 2002) companies have been slow to adopt it (Barratt and Oliveira, 2001). A case study by McCarthy and Golicic (2002) suggests that the CPFR process model may be too complicated and require too high an investment and that simpler collaboration models would work better. Barratt (2004) presents a very large number of potential inhibitors and enablers of collaboration, but does not prioritize among them. There, thus, remains a clear need for more empirical research in order to better understand the feasibility and value of forecasting collaboration in different situations and in different supply chains.

3 METHODOLOGY

3.1 Research questions

Based on the identified gaps in theory, the following three research questions were formulated:

Question 1: In what situations does sharing of downstream sales data with upstream supply chain members enable increased efficiency?

The first question (Question 1) is based on the observation that the situational factors affecting the value of information sharing are not sufficiently well understood. Previous studies have looked at different ways of making use of the data as well as examined the impact of some supply chain attributes, such as capacity, lead-times, and demand characteristics. Yet, the impact of many other factors, such as product characteristics or the proportion of customers involved in information-sharing efforts, is still poorly understood.

Furthermore, most of the research on information sharing to date has been conducted using analytical models with either stationary or auto-correlated demand processes. Although several authors suggest that sharing of sales data could be more valuable in situations of changing, irregular demand, very little research has focused on this particular area. There is a need for research examining what the value of information sharing is in situations of high demand uncertainty, such as product introductions or promotions.

Finally, the value of different kinds of sales data, such as customer sell-through or POS data, has been subject to surprisingly little research. It is often assumed that POS data is always the best option, but few studies have actually attempted to compare the different types of data and their usefulness from a production and inventory control point of view.

Question 2: What are the prerequisites for upstream supply chain members to be able to benefit from access to downstream sales data?

The second question (Question2) originates in the mixed experiences of companies that have implemented information-sharing practices, such as VMI. Although most of the research agrees that manufacturers are to benefit the most from information-sharing efforts, many manufacturers seem to have found it difficult to realize these benefits in practice. Yet, apart from the impact of manufacturer production capacity, the potential links between the manufacturers' operative processes and capabilities and the attainable benefits of information sharing have not been examined. The mechanisms enabling or hindering companies to benefit from access to downstream sales data are clearly not sufficiently well understood.

Question 3: What additional benefits and costs are associated with moving from sharing of downstream sales data to collaborative forecasting in supply chains?

The third question (Question 3) arises from the conflict between the academic literature and practice. Many academics argue that tightened supply chain integration in the form of collaborative forecasting would provide greater benefits than sharing of sales data, but companies have been slow to adopt forecasting collaboration. Although some attempts have been made to explain why implementation has been so difficult, the results to date have been long lists of potential problems, including many of the “usual suspects”, such as lack of trust or lack of shared targets. This makes it hard to discern whether forecasting collaboration has stumbled on traditional difficulties related to the implementation of new practices, or whether there are some inherent problems with the concept of collaborative forecasting.

Furthermore, the analytical models used to examine the value of forecasting collaboration seem to build on very strong assumptions. It is, for example, assumed that retailers are able to produce perfectly accurate and reliable forecasts and that the combination of retailer and supplier forecast information always improves the quality of the forecast. These assumptions have, however, not been empirically validated. More information on the soundness of these assumptions is needed. In addition, more empirical research on the potential benefits of forecasting collaboration would be valuable.

3.2 Research design

This thesis builds on results from six individual studies (see Figure 2). The first three studies examine the use and characteristics of different types of downstream sales data (Studies 1, 2 and 3) and focus on Questions 1 and 2. The three latter studies examine collaborative forecasting (Study 4) and contrast it with sharing of sales data (Studies 5 and 6) in order to answer Question 3.

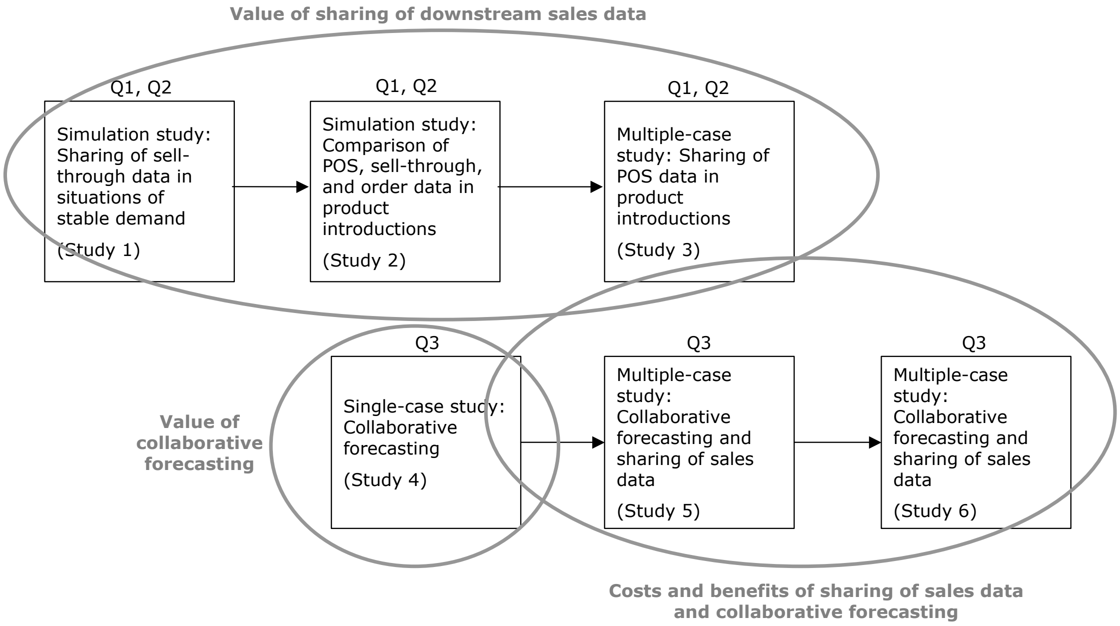

Figure 2. Research design.

3.3 Research methods

The research methods, data, and analyses employed in the studies are summarized in Table 4 and briefly discussed in the following text. The studies are presented in detail in Chapters 4 – 6.

3.3.1 Simulation studies

Analytical and simulation modeling are research methods that provide laboratory-like environments in which all variables can be controlled (Maloni and Benton, 1997). They also allow for the study of non-existent systems (Hoover and Perry, 1989). Therefore, these methods are very useful when examining the impact of different variables on the results or when doing initial testing of new ideas. Modeling, of course, comes with some limitations, as well. Efficient modeling requires simplification of the research context (McGrath, 1982), which means that new, unexpected variables usually cannot be detected, as in, for example, case research.

Compared to analytical modeling, simulation modeling is more flexible (Johnsson, 1992). Fewer limitations are imposed on the model since a numerical rather than an analytical approach is employed.

Table 4. Research methods, data and analyses.

	Research method	Sample	Data collection	Data	Analysis
Study 1	Simulation	Twenty-one products with stable demand	Discussions, data requests	Information on supply chain structure, distributor sales data, products' replenishment batch sizes	Impact of three factors on the attainable operational benefits of manufacturer access to distributor sell-through data
Study 2	Simulation	Seventeen product introductions	Discussions, data requests	Information on supply chain structure, POS data, products' replenishment batch and wholesale package sizes	Comparison of POS, distributor sell-through, and order data in view of delay and variability
Study 3	Multiple-case study	Two retailer-manufacturer relationships, 200 products	Direct observation, data requests, interviews	POS data, manufacturer forecast and inventory data, process information, opinions and experiences	Analysis of sales patterns, comparison of company experiences, identification of contingency factors
Study 4	Single-case study	One retailer–manufacturer relationship, 169 products	Interviews, data requests	Process information, manufacturer and retailer forecast data, retailer sales data	Comparisons of forecasting processes and forecast accuracies
Study 5	Multiple-case study	Four retailer–manufacturer relationships	Semi-structured interviews, direct observation, reports, presentations, informal discussions	Experiences and opinions, performance data, process information	Within-case analysis and cross-case pattern search based on four constructs
Study 6	Multiple-case study	Twelve retailers	In-depth structured interviews	Process information, performance data, opinions and experiences	Examination of generalizability of observations made in Study 5

However, analytical models tend to be more generalizable than simulation models as the relationships between different variables can be exactly defined. In simulation modeling, relationships between variables are typically established through statistical analysis of the results, which means that the identified links may be somewhat vague or even random. Simulation also identifies the best solution among the solutions that have been tried and is, therefore, limited in its ability to find the optimal solution (Mentzer, 1989).

In this thesis, simulation modeling is used in Study 1 to examine the impact of three variables on the value of information sharing and in Study 2 to compare three different kinds of sales data to examine demand signal distortion in the context of product introductions.

Study 1

Study 1 was set up to examine the impact of VMI, i.e. manufacturer access to distributor sell-through data, on the manufacturer's production and inventory control in a situation of stable demand. The simulation model was created to mirror an actual supply chain involving one manufacturer serving several retail distribution centers.

The study looks at the impact of three factors – replenishment frequency (the products' replenishment batch sizes compared to the products' average demand; twenty-one levels), VMI adoption (proportion of distribution centers involved in VMI relationships with the manufacturer; four levels) and production planning frequency (the length of the manufacturer's production and planning cycle; three levels) – on the bullwhip experienced by the manufacturer. Bullwhip is measured, as suggested by Fransoo and Wouters (2000), as the manufacturer's production variability compared with demand variability at the retail distribution centers.

The research was carried out in co-operation with two simulation experts and the author's dissertation advisor (see Appendix II for a detailed description of the co-operation). The simulation runs were conducted using actual distributor sell-through data and data on replenishment batch sizes for a set of twenty-one products and a period of sixty weeks. The data were collected from the manufacturer and the retail distribution center whose supply chain the model was designed to reflect. A total of 252 simulation runs were conducted in order to test all combinations of variables.

Choosing a modeling rather than an empirical approach in this study was a logical decision. A survey approach would have made it difficult to accurately understand the relationship between the different variables and the bullwhip effect. A case study approach, on the other hand, would not have allowed for systematic examination of all combinations of variables. The reason why simulation rather than analytical modeling was selected was mainly that a simulation approach enabled the use of a more realistic supply chain model and actual supply chain data in the analysis. The use of actual data made it possible to get plausible estimates of the attainable benefits of information sharing.

Study 2

Study 2 was set up to analyze and compare the characteristics of POS data, distributor sell-through data, and distributor orders for recently introduced products. The simulation model used in Study 2 is similar to the one used in Study 1. The main difference is that a number of retail outlets being served by the retail distribution centers have been added to the model.

Study 2 examines the amount and type of demand distortion induced by the different echelons of the supply chain and, based on this information, establishes the potential usefulness of the different types of sales data. The following metrics are used when comparing the demand signals: the bias and delay in conveying information on changing demand as well as the variability of demand. Study 2 also examines the impact of loading the supplier's production with sales data attained from the different sources.

The simulation model was created in co-operation with a simulation expert and the author's dissertation advisor (see Appendix II for a detailed description of the co-operation). The simulation runs were conducted using actual store-level POS data on seventeen product introductions by two manufacturers in three grocery chains. Data for a period of six months following the product launches were used. In addition, the products' wholesale package sizes as well as their replenishment batch sizes attained from the retailer and the manufacturers were used in the simulations.

Again, modeling was a natural choice for this kind of research since it makes it possible to control all relevant variables, which would have been impossible in empirical research. Simulation rather than analytical modeling was selected for two reasons: Firstly, the flexibility of the simulation approach was seen as an advantage. Simulation made it possible to construct the model without having to introduce limitations to make the calculations tractable. Secondly, simulation allowed for the use of actual supply chain data, including POS data on product introductions, in the study. This was considered important since there are no generally accepted approaches to modeling product introductions and since the irregularity of demand was considered a typical characteristic of product introductions that needed to be included in the model. However, the use of a simulation approach also presented some limitations. Statistical analysis of the relationships between the variables and the observed demand distortion was, in some cases, insufficient to establish the exact form of these relationships. From this point of view, analytical modeling would probably have produced more precise results.

3.3.2 Case studies

Case studies are recognized as being especially valuable in exploratory research looking for new variables and relationships. It is also a good approach when attempting to answer the question of why observed phenomena occur, especially when trying to understand non-standard forms of behavior. (Meredith, 1998; Stuart et al., 2002; Voss et al., 2002; Yin, 1989). Furthermore, the case study approach is a good choice when little previous empirical research is available on the subject (Eisenhardt, 1989).

The case study approach, however, also has some limitations. An important problem that has been much discussed in literature is the generalizability of the results of case study research (see, for example, Voss et al., 2002; Yin, 1989). Since the studies typically focus on only one or a few companies or organizations, it is sometimes difficult to know whether the identified relationships are somehow specific to the examined context or whether they are more general in nature. In addition, as there are typically vast amounts of data collected when conducting a case study and the researcher needs to make choices concerning what information to present, it may be difficult to confirm that the conclusions actually follow from the collected data (Meredith, 1998).

In this thesis, a case study approach is used in Studies 3 – 6. Study 3 examines how manufacturers can benefit from access to POS data in managing product introductions. Study 4 examines whether collaboration based on comparison of forecasts could improve the forecasting performance of a grocery retailer and a manufacturer. Study 5 looks at four retailer – manufacturer collaboration projects in order to compare the feasibility and value of information sharing and forecasting collaboration. Study 6 examines the generalizability of the observations made in Study 5 by collecting data on a larger, international sample of retailers.

Study 3

Study 3 was set up to examine how manufacturers are able to benefit in practice from access to POS data in managing product introductions. The study includes two manufacturers participating in an information-sharing effort with a retailer. By comparing the experiences and actions of the manufacturers, contingency factors having an impact on the value of information sharing are identified.

Study 3 consisted of several phases. First, historical POS data on product introductions was analyzed in order to better understand its potential usefulness in updating forecasts for recently introduced products. The analyzed sample included a total of 109 products representing three product categories. The results of the analyses were discussed with representatives of two manufacturers and one retailer. Based on these discussions, a pilot for testing the value of sharing of POS data for recently introduced products was designed. The author participated in the design of the pilot implementation. The pilot implementation included nineteen product introductions. During the pilot, the author participated in the manufacturers' forecasting meetings to monitor how the POS data was used and what kind of forecast updates its use resulted in. In addition, interviews with the manufacturers' key account managers and the retailer's logistics planners involved in the pilot were conducted. After the pilot, the companies decided to continue their co-operation on a permanent basis. Data on one of the manufacturer's forecast accuracy and customer service levels before and after the beginning of the co-operation were compared. Corresponding data from the other manufacturer was not available. Instead, an interview with the company's logistics manager was conducted.

A case study approach was chosen due to the exploratory nature of the research. Previous research on information sharing has focused on situations of stationary or auto-correlated demand and there is currently no established approach to modeling demand for recently introduced products. In addition, there is very little information on potential contingency factors having an impact on the feasibility or value of information sharing for recently introduced products, making it difficult to construct a useful model. In fact, Study 3 is a valuable complement to Study 2, as it includes many aspects, such as forecasting and production planning, that were considered too complex to include in the model used in Study 2.

It is important to notice that although Study 3 is labeled a case study, the role of the author in this study was more active than is typical in case research. The study could, in fact, be considered action research in the spirit of French and Bell's (1984) definition of the concept: systematically collecting research data about an existing system, taking action by altering selected variables with the system based on the data and on hypotheses, and by evaluating the impact of actions by collecting more data on the outcomes. However, the term action research is typically used when the effects of an intervention in individuals' or group behavior are studied (Kaplan, 1998). Here, rather than trying to change the behavior of people, the usefulness of a new information source in decision-making was examined. In addition, the original idea of analyzing the value of POS data in managing upstream operations came from the retailer rather than from the author. The research setting can, therefore, not be considered typical for action research either, which is why Study 3 has been labeled a case study in this thesis.

Regardless of the label put on the research, the question of researcher bias and independence arises when the researcher is personally involved in the study. To tackle this problem, the companies' and the author's different roles were defined and emphasized throughout the study. The author's role was to support the development process by providing data analyses, acting as a neutral referee ensuring that all parties' viewpoints were considered, and by acting as an unbiased observer when examining the impact of the information-sharing pilot and the subsequent process implementation. The companies' role was to make decisions concerning what ideas to implement, what information to share, and how the information-sharing process should be set up in practice.

Study 4

Study 4 was designed to examine the feasibility and value of collaborative forecasting in general, and the CPFR process model in particular. The study involved one grocery retailer and one manufacturer. The forecasting processes and forecast accuracy of the retailer and the manufacturer were examined in order to establish whether collaboration based on comparison of the two companies' forecasts could improve their forecasting performance.

Information on the retailer's forecasting process was collected through interviews with one of the retailer's category managers, an IT specialist, and the company's development and logistics manager. Information on the manufacturer's forecasting process was collected through interviews with a key account manager and the logistics manager. Forecast data were collected from the two companies' ERP systems and compared to actual sales data received from the retailer. The comparison included 169 products. The findings were discussed and validated in co-operation with retailer and manufacturer representatives.

Study 4 was somewhat action-oriented, although to a lesser extent than Study 3. The author's role was to act as an independent observer and to provide objective analysis of the potential value of CPFR-style forecasting collaboration and to present recommendations concerning the implementation of CPFR or some other kind of collaboration. Since the research was data-driven, the risk of the results being affected by researcher bias can be considered minimal.

The selection of an empirical research approach was logical. There are, in fact, many elements that make collaborative forecasting an ideal candidate for case research: the relevant variables and relationships explaining successful or unsuccessful forecasting collaboration have not been satisfactorily identified, companies seem to operate differently than suggested by theoretical models, and there is little previous empirical research on the topic. The case study approach was, therefore, adopted also in Studies 5 and 6.

Study 5

Study 5 was set up to examine and compare the benefits and costs associated with sharing of sales data and forecasting collaboration. In order to allow for more extensive cross-case analysis, the two cases on information sharing presented in Study 3 were complemented with two additional cases focusing on collaborative forecasting. A total of four retailer–manufacturer development efforts were, thus, examined.

The study followed Eisenhardt's (1989) process for case study research. First the individual cases were studied in-depth. Next, cross-case analysis took place, focusing on the following four constructs: the characteristics of the piloted collaboration practices (i.e. the contents and scope of the collaboration processes employed in the development projects), the benefits and costs of the piloted collaboration practices (both realized and expected), the relevance of the piloted collaboration practices to the companies involved (compared with other opportunities to work together), and the scale-up prospects of the piloted collaboration approaches. Finally, the detected patterns were presented in the form of three observations and compared to extant literature.

The data collection effort included interviews with company representatives (all cases), direct observation of project meetings or the collaboration process (three of the cases), project documentation (all cases), and data analyses (three of the cases). In addition, a workshop in which the companies' experiences of collaboration were discussed and analyzed was arranged.

Study 6

In order to examine the general validity of the observations made in Study 5, Study 6 was set up. Study 6 was conducted through in-depth interviews with twelve leading European grocery retailers. The interviews were structured and followed a detailed questionnaire, which had been tested on one of the respondents and then updated. In most of the companies, several interviews were conducted, either with the same person or several persons. The respondents were typically managers or directors of logistics and supply chain management, development, or information technology (IT). A total of twenty-one persons participated in the interviews.

To allow for triangulation, both quantitative data (such as data on inventory levels, service levels, and lead-times) and qualitative data (such as process descriptions, opinions, and experiences) were collected on five different topics: supply chain structure and performance, chain control, logistics processes (focusing on inventory management and forecasting), development opportunities in the area of logistics, and retailer-supplier collaboration. Based on the interviews, company-specific case descriptions were written.

These case descriptions were checked both by the researchers participating in the study and by the respondents. The data was then analyzed from the point of view of the observations presented in Study 5 to look for supporting or refuting evidence.

The study was carried out in co-operation with researchers from five European universities to enable interviews to be conducted in the interviewees' native languages and to be able to benefit from local contacts to industry (see Appendix II for a detailed description of the co-operation).

Since Study 6 was set up to examine the generalizability of the observations made in Study 5, a survey approach rather than in-depth interviews would perhaps have been the expected choice of research method. Yet, due to the detailed nature of the data needed as well as the lack of standardized terminology in the area of information sharing and forecasting collaboration, in-depth interviews were seen as a more reliable data collection tool than, for example, a postal survey, despite the limitations on sample size that it presents. However, it is clear that the small sample presented limits on the generalizability of the results as well as on how the data could be analyzed. Quantitative analysis was in general not possible.

3.4 Validity and reliability

Each of the research questions of this thesis is addressed in multiple studies. This allows for triangulation through the use of multiple data sources and different research methods (Jick, 1979).

Validity issues have also been addressed in the individual studies. In order to improve construct validity in the simulation studies, the most commonly used construct for operationalizing the bullwhip effect (or a slightly adapted version of it) has been used in Studies 1 and 2. In addition, the delay in demand synchronization metric used in Study 2 builds on the well-known concept of bias that is much used, for example, in assessing forecast quality (Vollmann et al., 1997).

To ensure a level of external validity, the supply chain models used in Studies 1 and 2 have been simplified to make them less company-specific. In their current form, the models portray general retail supply chains, which means that the results attained should be generalizable at least to other retail supply chains. The models are, in fact, quite similar to those traditionally used in analytical modeling of information sharing problems, but the use of simulation enables more realistic sales data and parameter settings to be used.

Although conducting multiple replications is a validation technique applicable only to stochastic simulation models, a certain degree of replication logic was present both in Study 1 and Study 2. In Study 1 all combinations of twenty-one products, four levels of VMI adoption, and three production planning frequencies were examined, resulting in a total of 252 simulation runs, i.e. several runs for each of the variable values. In Study 2, seventeen product introductions and several different inventory initializations at the retail and distribution echelons were examined, resulting in a total of 102 simulation runs, i.e. several runs for each of the variable values.

Reliability in the simulation studies has been addressed by providing detailed descriptions of how the simulation models are constructed. However, no attempt to verify the correctness of the models by comparing their results to data on real-life supply chains was made, although this is a verification technique much used in simulation. In Studies 1 and 2 the aim was not to recreate the supply chains used as the starting point as accurately as possible, but rather to create reasonably realistic, yet very much simplified models. Therefore, instead of verifying the models by making sure that they faithfully represent specific real-life supply chains, the simulation models and results were reviewed in co-operation with company representatives who validated the general logic of the models and the results that they produced. The models were also checked manually using spreadsheet software to verify the calculations for a sample of products and variable values.

In the case studies (Studies 3 – 6), the issue of construct validity has been addressed by having key informants review the case descriptions, as suggested by, for example, Stuart et al. (2002). In addition, multiple data sources, including interviews, performance data, and documentation, have been used in Studies 3, 4 and 5. In study 6, all data were collected through interviews, but questions approaching the same topic from different angles, e.g. through subjective opinions, performance data, and process descriptions, allowed for triangulation. In Studies 5 and 6, *a priori* constructs, as suggested by Eisenhardt (1989) were used. External validity was addressed by increasing the sample size when moving from Study 3 and 4 to Studies 5 and 6.

In the case studies, reliability has been addressed by making the questionnaires used available in Appendixes III and IV. In addition, an attempt to convey the richness of the data through inclusion of respondents' quotes has been made (Stake, 1994).

In the more action-oriented Studies 3 and 4, special care was taken to make sure that results were not influenced by the author's involvement in the projects. In Study 3, the use of quantitative performance data enabled objective analysis and triangulation. Both qualitative and quantitative information sources provided a similar image of the information-sharing effort, improving the reliability of the study. In addition, since both successes and difficulties were identified both through interviews and data analyses, it appears that results were not biased. In Study 4, the emphasis was on objective data analysis, whereas qualitative data was mainly used to understand the underlying processes causing the results of the analyses.

3.5 Co-operation with industry

The research presented in this thesis consists of empirical studies (Studies 3 – 6) as well as simulation studies based on actual supply chain data (Studies 1 and 2). In order to collect the necessary data and information, the author has worked together with several companies.

The first five studies were performed as part of two logistics research projects funded by the National Technology Agency of Finland (TEKES) and companies interested in monitoring or actively participating in the research. Working with companies involved in research projects ensured access to, among other things, confidential data on sales, promotions, and products, as well as information on the companies' development and collaboration efforts. Although the companies set some limitations on how the data could be used and communicated, e.g. sales data typically needed to be indexed not to reveal the actual volumes and exact company or product identities could not be revealed, no limitations on presenting the findings or conclusions were presented.

Studies 1 - 5 of this thesis are based on co-operation with four consumer goods manufacturers: CandyCo (Studies 1, 2, 3, and 5), ChemCo (Studies 2, 3, 4, and 5), DairyCo (Study 5), and MeatCo (Study 5). CandyCo is an international confectionary manufacturer with a very strong market position in the examined region. Some of its main production facilities are also located there. CandyCo is quite supply chain oriented and has invested in increasing the responsiveness of its operative processes. It is currently engaged in collaboration efforts both with its customers and its suppliers. ChemCo is a very large, multinational manufacturer of techno chemical products, such as personal hygiene and household cleaning products. It has specialized production plants in several countries serving many local markets. DairyCo is a national producer of dairy products. MeatCo is a national producer of meat products with a product offering ranging from packaged meat to ready meals.

The author has also worked together with two grocery retailers: TradeCo (Study 4) and RetailCo (Studies 3 and 5). The retailers are rather similar in that they both operate several chains of stores, ranging from small neighborhood stores to larger hypermarkets. However, whereas TradeCo is one of the market leaders in the examined region, RetailCo can be considered a challenger, although it is clearly one of the main players in the market. RetailCo is considered very supply chain oriented. In the late 1990's, RetailCo got interested in CPFR among the first in its market and has since then been involved in several collaboration projects.

Finally, Study 6 was conducted as part of a research project fully funded by TEKES. The study consisted of interviews with twelve leading grocery retailers representing six countries from the following regions: the Nordic countries, the UK, Northern Continental Europe, Western Continental Europe, Central Continental Europe, and Southern Continental Europe. None of the companies were directly involved in the research project. They were rewarded for their participation in the study by giving them access to a detailed report of the results of the interviews. The lack of direct involvement in the research project, however, did have an impact on the quality of the data collected from the companies; although some companies provided very detailed and accurate data, a few companies provided somewhat vague and general information and were reluctant to spend time filling in missing information. All of the companies expressed a wish to remain anonymous and some demanded that countries should not be disclosed. Otherwise, no limitations on presenting the results were set by the companies.

4 STUDIES ON INFORMATION SHARING

4.1 Value of manufacturer access to sell-through data for products with stable demand (Study 1)*

4.1.1 Purpose of the study

Study 1 provides answers to Question 1: In what situations does sharing of downstream sales data with upstream supply chain members enable increased efficiency? and Question 2: What are the prerequisites for upstream supply chain members to be able to benefit from access to downstream sales data?

More precisely, the study examines the value of manufacturer access to distributor sell-through data for products with reasonably level demand. The impact of three factors – the proportion of customers giving the manufacturer access to their sell-through data, the replenishment frequencies of the products, and the manufacturer's production and planning frequency – on the value of information sharing is examined.

The first factor was included in the examination because previous research by Vergin and Barr (1999) has suggested that the low proportion of customers providing sell-through data may be an important reason why manufacturers have found it difficult to benefit from information-sharing efforts such as VMI. Inclusion of the second factor in the analysis was motivated partly by the finding of Cachon and Fisher (2000) that more frequent ordering is more beneficial than information sharing and partly by the findings of Kaipia et al. (2002) and Chen (1998) that information sharing is more valuable for products with low replenishment frequencies and high levels of batching. Finally, the third factor was included due to the necessity of specifying the production planning frequency in the simulation model and the knowledge that a wide array of different planning cycles are used by companies.

4.1.2 Methodology

The study was conducted using discrete-event, deterministic simulation. Deterministic means that the results of the simulation runs follow directly from the chosen parameter settings and the data inserted into the model. Multiple runs using the same parameter settings and the same input data, thus, produce exactly the same results, as the model does not have any stochastic features.

*Results from this study have previously been presented in Småros J., Lehtonen, J-M., Appelqvist, P., Holmström, J. (2003), "The impact of increasing visibility on production and inventory control efficiency", International Journal of Physical Distribution & Logistics Management, Vol. 33, Iss. 4, pp. 336-354.

Due to the deterministic nature of the model, the validation technique of conducting several replications of the simulation runs was not applicable. However, replication logic was still present to a degree. Since simulation runs were carried out for all combinations of twenty-one products, four levels of VMI adoption, as well as three different planning frequencies, a total of 252 simulation runs were performed, which means that several runs for each product and parameter value were conducted.

To make the simulation model more realistic, it was designed to mirror the supply chain of a consumer goods manufacturer, CandyCo, involved in VMI. Actual sell-through data from CandyCo's VMI implementation as well as actual product information was used in the simulations. This means that a certain level of randomness was included in the simulations, as the sales data were not drawn from any pre-defined distribution but originated in a real-life case. The use of CandyCo's data in the study was motivated by CandyCo's interest in the research. The company currently has a VMI agreement with one of its largest customers, but also serves several non-VMI customers. The VMI implementation has already proven valuable both to CandyCo and to the distributor participating in the arrangement. VMI has, among other things, reduced the distributor's workload and improved communication between the companies. Still, CandyCo believes that additional benefits could be attained if the sell-through data available through VMI could be used more effectively in its production and inventory control.

In simulation studies, a typical approach used for verifying that the model works as it is supposed to is to compare the results that it produces with data on the real-life system. However, in this study, the aim was not to accurately recreate CandyCo's supply chain. Instead, the aim was to create a fairly realistic, yet very much simplified model that could provide more general results. No attempt was made to include aspects, such as realistic forecasting or production scheduling, in the model. Therefore, rather than validating the model by making sure that it accurately reflects the real-life supply chain, the simulation model and results were reviewed in co-operation with representatives of CandyCo who validated the general logic of the model and the results it produced. In addition, manual checks using spreadsheet software were carried out to verify the results for a sample of products and parameter settings.

Simulation model and data

The supply chain model used in the simulations consists of one manufacturer serving three distributors, which in turn serve several retail outlets. Although Figure 3 illustrates a situation where one of the distributors is involved in VMI and the other two employ traditional orders, all levels of VMI adoption– zero, one, two or three VMI distributors - are examined.

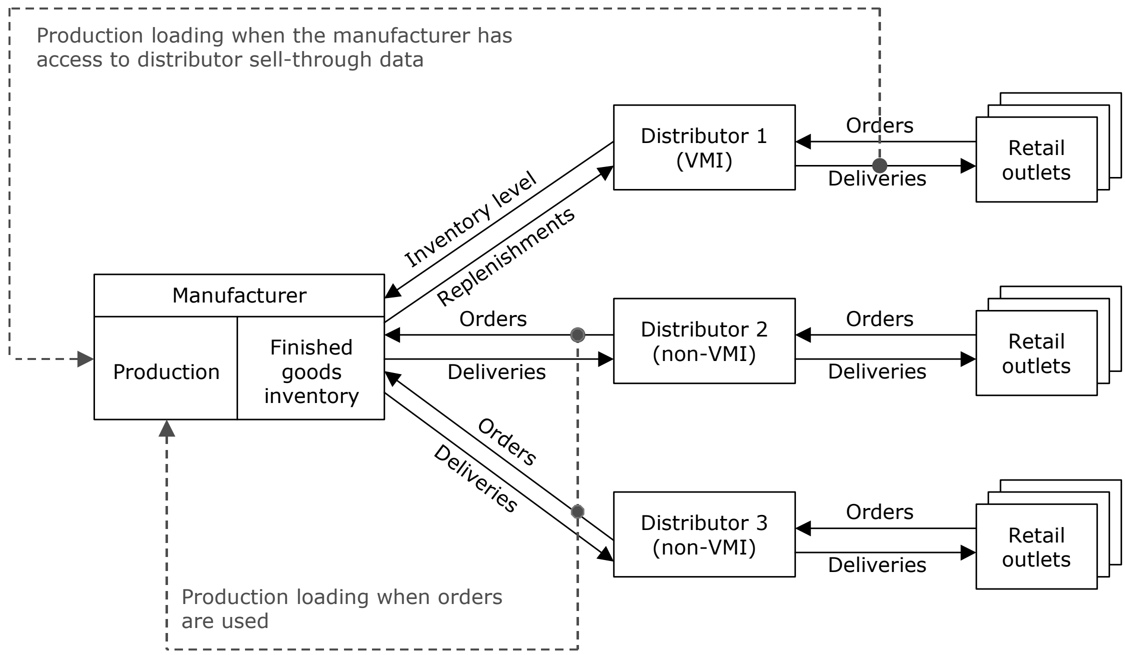

Figure 3. Supply chain model used in Study 1.

In the model, the retail outlets order products from the distributors daily. Actual distributor sell-through data from CandyCo's VMI implementation was used to model the retail outlets' orders. From a sixty-week period of daily sell-through data, ranging from March 2001 to May 2002, mature products with reasonably level demand and belonging to one of CandyCo's most important product categories were selected. Seasonal products and products introduced or discontinued during the observed period were discarded.

The selected sample included products with different demand volumes, the best selling product having almost twenty times the sales of the least selling product (measured in units). In addition, there were differences in demand variability; the relative standard deviation of the products' daily sell-through data varied from 65% to 213%, and the relative standard deviation of the weekly sell-through data varied from 17% to 80%. However, based on a graphical examination, sales for almost all products appeared to be roughly normally distributed, although some of the products did have heavy right-hand tails. There were also differences in the products' replenishment frequencies. The replenishment frequencies varied between 1,5 replenishments per week on average and 4,5 replenishments per week (i.e. almost daily replenishment) on average.

To model multiple distributors, the original sell-through data series was divided into three twenty-week sections, which were then used as the demand for the three distributors in the simulation model. The resulting demand pattern is reasonably realistic as the VMI distributor stands for approximately one third of the case manufacturer's total sales and as the ordering patterns of the different retail outlets can be assumed to be quite similar.

In the model, the distributors fulfill the retail outlets' orders as they are received. The distributors' inventories are managed using a re-order point control mechanism. For non-VMI distributors this means that they place orders when a product's inventory level has dropped below a specified re-order point. For VMI distributors, the manufacturer monitors the distributors' inventories and ships replenishments when the re-order points have been reached. The orders are multiples of the distribution batch size for each of the products and the amount ordered is the number of batches needed to bring the inventory level back above the re-order point.

For both VMI and non-VMI customers, the re-order points were determined using an iterative, manual process. First, an initial value was given to the re-order point based on standard safety stock calculations assuming normally distributed forecast errors (Vollmann et al., 1997):

$$ROP = \overline{d} + Z(1{,}25 \cdot MAD), \tag{3}$$

where	d	=	product's demand during the replenishment lead time,
	Z	=	value from a table of standard normal distribution probabilities corresponding to the desired service level (here 99%),
	MAD	=	mean absolute deviation of demand.

Then, to ensure that no stock-outs occur, iterative simulation runs in which the products' individual re-order points were gradually increased were conducted until re-order point levels guaranteeing a 100% service level were found. This approach clearly results in unrealistically high re-order points and inventory levels. However, the inventory levels have no impact on the results of this study as long as no stock-outs occur. The relevant parameters are, instead, the product-specific replenishment quantities.

In reality, the inventory control parameters would be regularly updated based on forecast information. However, since only products with reasonably stable demand were selected for examination, both parameter updates and forecasts could be omitted from the model. In addition, in the model, the re-order points and inventory control logic of the distributors are unaffected by their status as VMI or non-VMI distributors, although, in reality, the inventory control parameters in VMI would be determined by the manufacturer and the VMI distributor jointly.

Since identical re-order point logic is used for controlling the inventories of both non-VMI and VMI distributors, the only difference between these two types of distributors from the model's point of view lies in how the manufacturer's production is loaded, i.e. what demand information drives production decisions. For production scheduling the manufacturer uses the period batch control for standard products presented by Burbidge

(1994). When orders are employed, the production load for one period consists of the orders received from the distributors during the previous period. In the case of VMI, the manufacturer's production load for one period is determined based on the distributor's deliveries to the retail outlets, i.e. sell-through data, during the previous period. When serving a combination of non-VMI and VMI distributors, the manufacturer's production load is formed by adding together orders from non-VMI distributors and sell-through data from VMI distributors.

The manufacturer ships products to the distributors on a daily basis according to orders or determined replenishment needs. In the simulation runs, a weekly, bi-weekly or monthly planning and production cycle is employed. Manufacturing is not capacity constrained. In the beginning of each simulation run, the manufacturer's safety stock is initialized to be high enough so that all orders and replenishment requirements can be fulfilled. Again, iterative simulation runs are used to identify this level of safety stock. The exact amount of inventory does not impact on the results as long as no stock-outs occur.

Variables

The study looks at the impact of three variables on the bullwhip experienced by the manufacturer. Firstly, the impact of the level of VMI adoption among the distributors on the manufacturer's production is examined. This is done by increasing the number of VMI distributors one by one and by measuring the impact on the manufacturer's production load variability. Secondly, twenty-one products are examined to establish how a product's replenishment frequency as determined by its average demand in relation to its minimum replenishment batch size affects the value of information sharing. Thirdly, three different production planning cycle lengths – one week, two weeks and four weeks – and their impact on the value of increased demand visibility are examined. In order to study all combinations of variables, a total of 252 simulation runs were conducted (see Figure 4).

VMI adoption among distributors		**Product's replenishment frequency**		**Manufacturer's production planning cycle**	
4 situations: no VMI customers, 1/3 VMI customers, 2/3 VMI customers, and all customers involved in VMI	x	21 products with replenishment frequencies ranging from 1,5 to 4,5 replenishments per week on average	x	3 planning cycle lengths: one week, two weeks, and four weeks	= 252 simulation runs

Figure 4. Simulation runs conducted in Study 1.

The dependent variable, bullwhip, is measured as the relative or absolute standard deviation of the manufacturer's production load. Bullwhip is defined by Fransoo and Wouters (2000) as:

$$bullwhip = \frac{c_{out}}{c_{in}}, \tag{1}$$

where c_{out} and c_{in} represent the relative standard deviation of demand measured upstream in the supply chain and downstream in the supply chain, respectively. The relative standard deviation c is defined as the standard deviation (σ) of demand (D) divided with the mean demand (μ) for a specified time interval [t, t+T]:

$$c = \frac{\sigma(D(t, t+T))}{\mu(D(t, t+T))}. \tag{2}$$

In this study, c_{in} is the relative standard deviation of demand at the distributors, i.e. the orders placed by the retail outlets, and c_{out} is the relative standard deviation of demand at the manufacturer, i.e. the orders placed by non-VMI distributors and the sell-through data of the VMI distributors. Since the manufacturer's production is unconstrained and loaded directly with the demand, the relative standard deviation of the production load is equal to c_{out}. In addition, since the same retail outlet demand data is used in all simulation runs, c_{in} does not change between runs and does not need to be discussed when presenting the results. Therefore, from here on, the standard deviation of the production load, either relative or absolute, will be used to express the different factors' impact on the manufacturer's production and inventory control efficiency. Reducing production load standard deviation is key to achieving lower inventories, improving delivery accuracy and improving capacity utilization.

4.1.3 Results

Impact of increasing VMI adoption

The impact of the level of VMI adoption on the manufacturer's production load variability was examined by increasing the number of VMI distributors one by one. Although the simulations were conducted for three different production planning cycle lengths, only the results attained using the shortest planning cycle are presented here. The impact of the manufacturer's planning cycle length on the value of access to sell-through data is discussed in a later section.

Table 5. Change in weekly standard deviation of production load (i.e. bullwhip experienced by manufacturer) compared to the base case of no distributors being involved in VMI.

	Change in bullwhip		
	1/3 VMI	**2/3 VMI**	**All VMI**
Product 20	-33 %	-45 %	-44 %
Product 11	-24 %	-37 %	-40 %
Product 17	-23 %	-37 %	-45 %
Product 5	-23 %	-34 %	-54 %
Product 7	-18 %	-34 %	-48 %
Product 15	-18 %	-20 %	-40 %
Product 19	-17 %	-32 %	-46 %
Product 4	-16 %	-26 %	-44 %
Product 12	-16 %	-31 %	-37 %
Product 9	-16 %	-29 %	-65 %
Product 3	-13 %	-18 %	-44 %
Product 2	-13 %	-11 %	-31 %
Product 13	-13 %	-39 %	-49 %
Product 21	-11 %	-27 %	-43 %
Product 10	-8 %	-20 %	-24 %
Product 14	-6 %	-28 %	-24 %
Product 18	-5 %	-13 %	-39 %
Product 8	-5 %	-28 %	-29 %
Product 16	-5 %	-25 %	-40 %
Product 6	-4 %	-26 %	-45 %
Product 1	-2 %	-20 %	-30 %
Average change	-14 %	-28 %	-41 %
Minimum change	-2 %	-11 %	-24 %
Maximum change	-33 %	-45 %	-65 %

The first change from no VMI distributors to one VMI distributor results in a moderate average reduction of production load variability. The average variability reduction is 14%, but there are noticeable differences between the individual products. For some products, the reduction is not important, only a few percent, whereas the maximum reduction is over 30%.

Next, the number of VMI distributors is increased to two, resulting in two-thirds of the manufacturer's production requirements being based on distributor sell-through data and one-third on traditional orders. The effect on production load variability is notable.

Compared to the base case of no VMI distributors, the reduction in production standard deviation is on average 28% for the products examined.

The full adoption scenario, i.e. all three distributors involved in VMI, further reduces variability. Compared to the base case of no VMI distributors, full adoption reduces production load standard deviation with 41% on average. The results are, once again, different for different products. The smallest reduction is, however, over 20% and the largest as much as 65%.

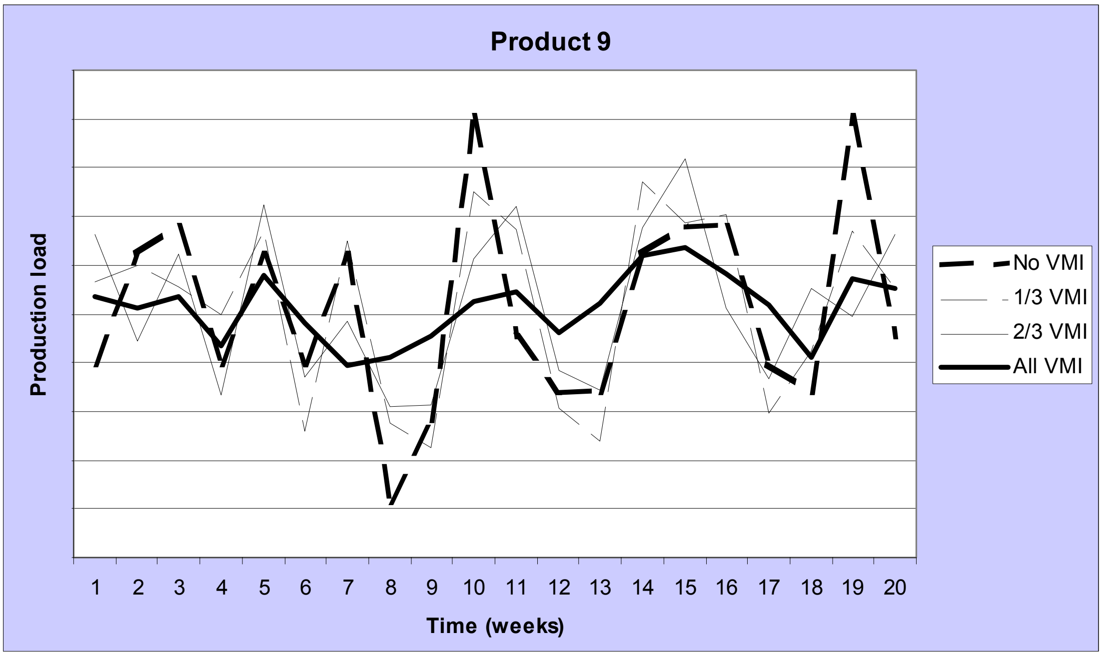

Figure 5. Manufacturer's production load at different levels of VMI adoption for an example product.

Figure 5 illustrates what happens when the number of VMI distributors increases. As more distributors get involved in VMI, the manufacturer can to an increasing extent use the less variable sell-through data rather than the more variable order data as the basis for its production and inventory control. This means that the distorting effect of distributor order batching is removed, leveling out the highest peaks and lowest valleys in demand. Of course, due to natural variation in demand as well as order batching at the retail outlets, some variation still remains in the data even in the situation of all distributors being involved in VMI.

Impact of products' replenishment frequencies

When assessing the effect of increasing VMI adoption on the manufacturer's production load variability, considerable differences between the products were observed. Whereas the reduction in variability for some products was remarkable, up to 65%, for other products the value of information sharing seemed much smaller.

In order to examine these differences a bit closer, we focus on two characteristics differentiating between the products: the products' average demand and their minimum replenishment batch sizes. By plotting the change in production load variability against a combination of these characteristics – the average number of replenishments per week – a pattern can be detected. This pattern shows that the impact of information sharing is, in general, greater for products with low replenishment frequencies, i.e. typically C-products, than for products with high replenishment frequencies, i.e. typically A-products. This is illustrated graphically in Figure 6 for the change from no distributors being involved in VMI to full VMI adoption among the distributors.

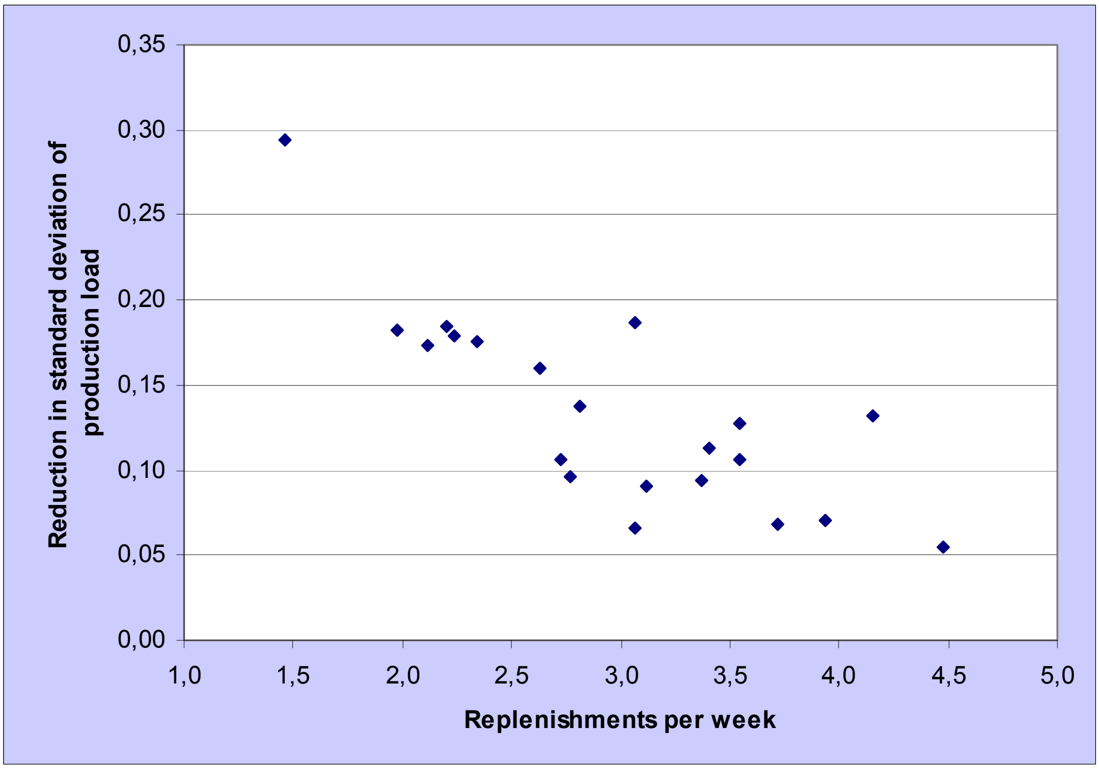

Figure 6. Impact of access to distributor sell-through data on manufacturer's production load variability for products with different replenishment frequencies. (Each dot represents one product).

The most important benefit of distributor sell-through data when compared to traditional orders is that one level of order batching is removed. This means that the impact of access to distributor sell-through data is typically greater for products with significant order batching, i.e. products whose minimum replenishment batches are large in proportion to their average daily or weekly demand. For these products, access to distributor sell-through data significantly speeds up the information flow within the supply chain. For products with high replenishment frequencies, the change is less dramatic. As can be seen in Table 6, an increase in demand visibility reduces the production load variability for all products. However, the change is larger for the products with low replenishment frequencies than those with high replenishment frequencies.

When the proportion of VMI distributors is high, the production loads of all products behave similarly.

Table 6. Relative weekly standard deviation of manufacturer's production load for products with different replenishment frequencies at different levels of VMI adoption.

		Relative standard deviation of production load			
	Replenishments per week	No VMI	1/3 VMI	2/3 VMI	All VMI
Product 14	1,5	44 %	37 %	31 %	15 %
Product 20	2,0	41 %	36 %	29 %	23 %
Product 8	2,1	41 %	38 %	30 %	23 %
Product 1	2,2	39 %	32 %	26 %	21 %
Product 6	2,2	35 %	31 %	21 %	18 %
Product 18	2,3	38 %	32 %	28 %	21 %
Product 17	2,6	33 %	27 %	22 %	17 %
Product 15	2,7	26 %	19 %	16 %	15 %
Product 10	2,8	25 %	21 %	17 %	15 %
Product 5	2,8	30 %	26 %	24 %	16 %
Product 2	3,1	21 %	18 %	18 %	14 %
Product 3	3,1	34 %	26 %	22 %	15 %
Product 12	3,1	35 %	32 %	28 %	26 %
Product 11	3,4	23 %	18 %	18 %	13 %
Product 7	3,4	25 %	19 %	15 %	13 %
Product 4	3,5	27 %	25 %	23 %	16 %
Product 13	3,5	28 %	27 %	21 %	15 %
Product 19	3,7	22 %	22 %	18 %	15 %
Product 16	3,9	23 %	22 %	16 %	16 %
Product 21	4,2	28 %	18 %	15 %	15 %
Product 9	4,5	22 %	20 %	16 %	16 %
Average		30 %	26 %	22 %	17 %
Standard deviation		7 pp	7 pp	5 pp	4 pp

pp = percentage points

Impact of manufacturer's production planning frequency

Finally, we examine the impact of the manufacturer's production planning frequency on the value of information sharing. Although some companies employ a weekly planning cycle, or even a daily planning cycle, many companies still use a longer, monthly planning cycle that enables them to optimize production capacity utilization. The relationship between planning cycle length and value of information sharing is, therefore, of great practical interest.

In order to examine this relationship, simulation runs with three different planning cycle lengths were conducted. Flexible production employing a weekly planning cycle was contrasted with less flexible production using planning cycles of two weeks and one month (see Table 7).

Table 7. Relative weekly standard deviation of the manufacturer's production load when employing a weekly, bi-weekly or monthly planning cycle at different levels of VMI adoption.

	Relative standard deviation of production load (standard deviation of results)		
	Weekly planning	**Bi-weekly planning**	**Monthly planning**
No VMI	30 % (7 pp)	21 % (6 pp)	13 % (4 pp)
1/3 VMI	26 % (7 pp)	19 % (5 pp)	11 % (4 pp)
2/3 VMI	22 % (5 pp)	17 % (4 pp)	10 % (3 pp)
All VMI	17 % (4 pp)	14 % (3 pp)	9 % (2 pp)

pp = percentage points

The analysis shows that the three situations differ right from the start. When using traditional orders, the relative standard deviation of the production load is on average 30% for the weekly planning cycle. When using a two-week cycle, the average relative standard deviation is smaller, around 21%. Finally, a monthly planning cycle reduces deviation even further, down to an average of 13%. These figures show how the importance of the order-batching phenomenon is reduced when using a longer production planning cycle. The long planning period also smoothens out variation between weeks.

Against this background, it comes as no surprise that the simulation results indicate that, other things being equal, information sharing is more valuable when using a shorter production planning cycle. The average reduction in production load standard deviation when moving from a situation with no VMI distributors to full VMI adoption is 41% when using a weekly planning cycle, whereas it is only 29% for the two longer production cycles. That is, when full adoption of VMI reduces the average production load variability from 30% to 17% for the weekly planning cycle, the reduction is from 21% to 14% for the bi-weekly planning cycle, and from 13% to 9% for the monthly planning cycle (see Table 7).

4.1.4 Conclusions

In relation to Question 1 concerning the situations in which access to downstream sales data is most valuable, Study 1 shows that by combining traditional order data with sell-through data available from VMI customers, manufacturers can benefit even when only part of the customer base is involved in sharing of downstream sales data. The benefits, however, increase when the adoption of VMI increases. These findings neither support nor refute the suggestion presented by Vergin and Barr (1999) that low VMI adoption – 20% on average in their study – may explain why manufacturers have found it difficult to benefit from VMI.

The results of Study 1 indicate that sharing of downstream sales data is likely to be more valuable for products with low replenishment frequencies. This result is in accordance with the findings of Kaipia et al. (2002), who used standard safety stock and re-order point formulas to develop a measure for the value of information sharing and made similar observations regarding the impact of replenishment frequency. The result is also congruent with the finding of Cachon and Fisher (2000) that for stationary demand the impact of more frequent ordering typically outweighs the benefits of access to downstream sales data. This study demonstrates that information sharing and high replenishment frequency have a similar impact on the manufacturer's production and inventory control efficiency.

In relation to Question 2 concerning the prerequisites for upstream supply chain members to be able to benefit from access to downstream sales data, the important impact of the manufacturer's production planning cycle was discovered. Order batching and, therefore, demand variability amplification are more important problems when short planning cycles are used. This means that manufacturers employing short planning and production cycles are likely to benefit more from information sharing efforts than manufacturers with longer planning cycles. This is an important observation since the role of production planning frequency has not previously been recognized in the literature on information sharing.

4.2 Comparison of POS, sell-through and order data for new products (Study 2)*

4.2.1 Purpose of the study

Study 2 provides answers to Question 1: In what situations does sharing of downstream sales data with upstream supply chain members enable increased efficiency? It also sheds light on Question 2: What are the prerequisites for upstream supply chain members to be able to benefit from access to downstream sales data?

More precisely, the study examines the value of manufacturer access to different kinds of downstream sales data in managing product introductions. By comparing POS data, distributor sell-through data, and distributor order data, the study examines how the demand signal is distorted by the echelons in a supply chain. Based on this information, conclusions concerning which information sources are most valuable when there are delays or variability amplification in a supply chain are presented. In addition, the study examines how downstream sales data can be used in controlling manufacturer inventory and production for recently introduced products.

Product introductions were selected for examination because it has been suggested that information sharing could be of greater value in situations of changing, unknown demand, such as promotions or product introductions (Cachon and Fisher, 2000). Different kinds of sales data were included in the analysis to enable further examination of the observation made by Fransoo and Wouters (2000) that different echelons of the supply chain may have different distorting effects on the demand signal and to make it possible to examine the claims presented by, for example, Kiely (1998) that companies should base their forecasts and production plans on POS data whenever possible.

4.2.2 Methodology

Study 2 was conducted using discrete-event, deterministic simulation. Deterministic refers to the fact that the results of the simulation runs follow directly from the chosen parameter settings and the data inserted into the model. Multiple runs using the same parameter settings and the same input data, thus, produce exactly the same results since the model does not include any stochastic features.

Due to the deterministic nature of the model, the technique of conducting several replications of the simulation runs to validate the results was not applicable. However,

*Results from an initial version of this study have previously been presented in Lehtonen, J-M., Småros, J., Holmström, J. (2005), "The effect of demand visibility in product introductions", International Journal of Physical Distribution & Logistics Management, Vol. 35, No. 2, pp. 101-115.

since simulation runs were conducted for seventeen products and several different combinations of parameters, resulting in a total of 102 simulation runs, replication logic was still present to a degree.

As in Study 1, the simulation model was designed to mirror an actual grocery supply chain. To overcome the problem of modeling transient, irregular demand, authentic POS and product data for seventeen product introductions were used in the simulation runs. This means that a certain level of randomness was included in the modeling, as the sales data was not drawn from any pre-defined, known distribution.

In simulation studies, a typical approach used for validating the model is to compare the results that it produces with data on the real-life system. However, in this study, the aim was not to accurately recreate the supply chain used as a starting point. Instead, the aim was to create a fairly realistic, yet very much simplified model that could provide more general results. No attempt was made to include aspects such as realistic forecasting or production scheduling into the model. Therefore, rather than validating the model by making sure that it accurately reflects the real-life supply chain, the simulation model and results were reviewed in co-operation with company representatives who validated the general logic of the model and the results it produced.

Simulation model and data

The supply chain model used in the simulations consists of a manufacturer serving three distributors, which, in turn, serve a large number of retail outlets including hypermarkets, supermarkets, and neighborhood stores (see Figure 7). The model is very similar to the one used in Study 1. The main difference is that the retail outlets have been explicitly modeled. In addition, the demand information fed into the model is POS data, i.e. consumer purchases, rather than retail outlets' orders.

As the study examines product introductions, the standard approach of analyzing a steady-state situation is not applicable. In fact, due to the transient nature of product introductions, the initial conditions of the supply chain cannot be omitted from the examination. In this study, the impact of the initial stock level at the retail outlets is examined by changing it from one full wholesale package above the re-order point to half a wholesale package above the re-order point, and, finally, to a third of a wholesale package above the re-order point. The impact of the initial stock levels at the distributors is examined by first initializing it to one full distribution batch above the re-order point and then to one third of a distribution batch above the re-order point.

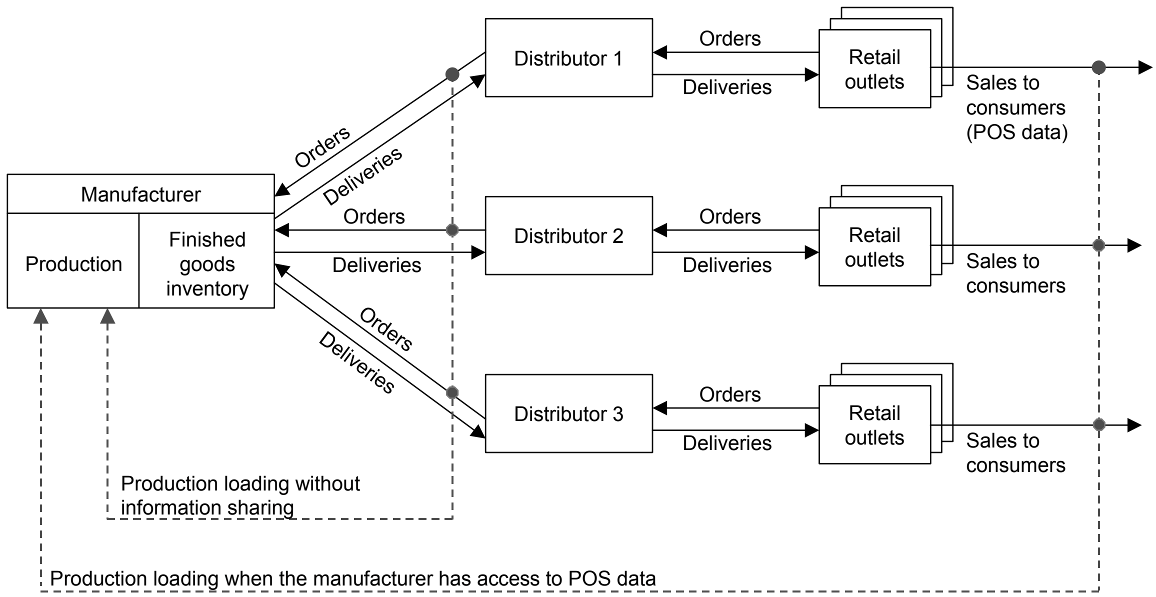

Figure 7. Supply chain model used in Study 2.

The examination, thus, begins with all echelons stocked. This means that the channel fill-up stage in the beginning of the product launch is omitted from the examination. This also makes it possible to use a pull-based rather than a push-based replenishment strategy in the simulation runs.

In the model, consumers purchase goods from the retail outlets daily. In the simulation runs, actual POS data on seventeen product introductions by CandyCo, a manufacturer of confectionery products, and ChemCo, a manufacturer of personal hygiene and household cleaning products, in three grocery retail chains are used. Daily, store-level POS data for a period of six months, i.e. 182 days, following the products' launch dates are used.

The examined products were introduced to the market in the fall of 2002. All of CandyCo's major product introductions in all of its categories were included in the examination, producing a sample of rather different products, including novelties (totally new kinds of products) and line extensions (new product variants added to existing product lines). The selection of ChemCo's products was conducted by company representatives to ensure a balanced sample including high- and low-volume products, different types of products, as well as different degrees of innovativeness of the introductions.

The examined products differ in sales volume, with total unit sales of the highest volume products being more than thirty times as large as sales of the lowest volume product. In addition, the size of the products' wholesale packages, measured in average days of supply (DOS) at the retail outlets, ranges from four days to over 100 days. The products' replenishment batch sizes, measured in average days of supply at the distributors, also range from four days to almost 150 days. Finally, the products' sales develop rather differently over the observed period. A seven-day moving average of the indexed sales (the index 100 was given to the maximum daily sales during the observation period) for the 100 first days following the introduction of six different products are presented in Figure 8. While sales of some of the products grow quite steadily, many products have highly variable sales, and for some products sales start to decrease soon after an initial demand peak.

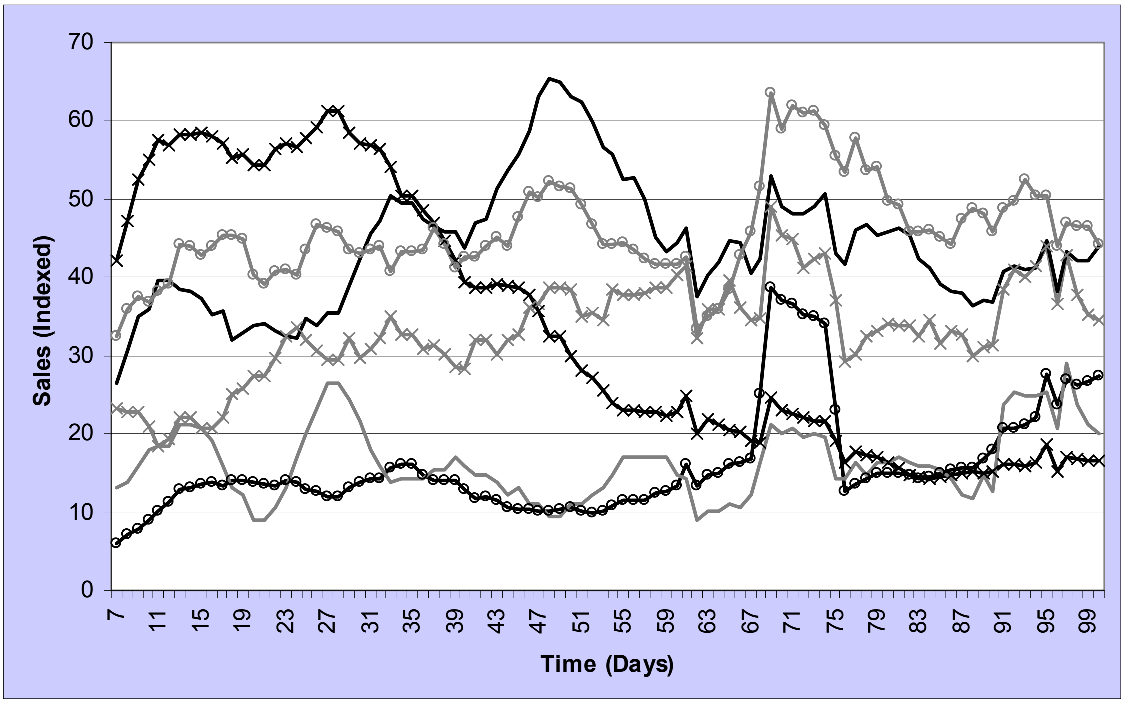

Figure 8. Sales profiles for six example products.

The retail outlets' as well as the distributors' inventories are controlled using re-order point logic with replenishment size of one, i.e. lot-for-lot replenishment. In the interface between the retail outlets and the distributors, the products' actual wholesale package sizes (typically cases) are used. In the interface between the distributors and the manufacturer, the products' actual distribution batch sizes (typically pallets) divided by three (to reflect the fact that, in reality, the three chains are served by just one distributor, not three as in the simulation model used here) are used. The replenishment orders are always placed at the end of the day. Replenishments arrive after a one-day transportation time lag.

The manufacturer's production cycle length is seven days. After that time, the products appear in the finished goods inventory and can be delivered to the distributors. It is assumed that there is infinite production capacity.

The retail outlets' and distributors' re-order points and the manufacturer's initial finished goods inventory are set to be sufficiently high so that no stock-outs are experienced. The re-order points and safety stock levels are set using a similar iterative, manual process as in Study 1, i.e. the re-order points and inventory levels are gradually increased until no stock-outs occur in the simulation runs. The safety stock levels at the different echelons of the supply chain do not affect the replenishment orders or the results of the simulation runs as long as no stock-outs are experienced.

Information sharing in the model is implemented by giving the manufacturer access to aggregate POS data, i.e. daily data on total consumer purchases at the retail outlets. Although there are several ways in which the manufacturer could potentially make use of this demand visibility, the approach used in this study is a simple base stock control algorithm (Silver et al., 1998), the same approach that was used in Study 1. That is, when there is information sharing, the manufacturer's production load for one period is determined based on aggregate POS data received from the retail outlets during the previous period. In the traditional supply chain setting where there is no information sharing, the production load for one period consists of the orders received from the distributors during the previous period. When examining the impact of information sharing on the manufacturer's production and inventory control, the following inventory initialization's are used: the retail outlets are stocked with a full wholesale package above the re-order point and the distributors are stocked with the amount of product corresponding to the re-order point rounded up to the nearest multiple of the distribution batch size. These were considered the most realistic initialization values.

Measures of information quality

The quality of the demand information available at the different echelons of a supply chain is typically evaluated by comparing demand variability at the different stages. However, the transient nature of demand in the context of product introductions makes measuring demand variability somewhat complicated. Here, demand variability is calculated in three steps: First, the daily POS data is subtracted from the daily order data (i.e. either from the orders placed by the retail outlets or from the orders placed by the distributors) in order to remove the growing trend and other irregularities. Next, the daily differences between the data series to be compared are summed up over each week. Finally, the standard deviation (δ) of these weekly sums is calculated. Depending on which data series are compared, the resulting measure is either an estimator of the variability of the retail outlets' orders (δ_R) or of the variability of the distributors' orders (δ_D). The increase in demand variability induced by the distributors ($\Delta\delta_{D/R} = (\delta_D / \delta_R) - 1$) is also calculated.

Another approach to assessing the quality of information is estimating the bias of data series. Bias measures whether there is a consistent difference between two data series, i.e. whether one of the series generally tends to include higher or lower values than the other series. It is often used to assess forecast quality (Vollmann et al., 1997). Here, bias is calculated as the cumulative difference between two demand series. The measure is scaled by dividing the calculated difference with the cumulative end consumer demand, i.e. the cumulative POS data, for the entire simulation run. Two different bias measures are used (Figure 9): Retail bias ($Bias_{CvsR}$) is the cumulative, scaled difference between consumer purchases at the retail outlets (i.e. the aggregate POS data) and the retail outlets' orders to the distributors; total bias ($Bias_{CvsD}$) is the cumulative scaled difference between consumer purchases at the retail outlets and the distributors' orders to the manufacturer.

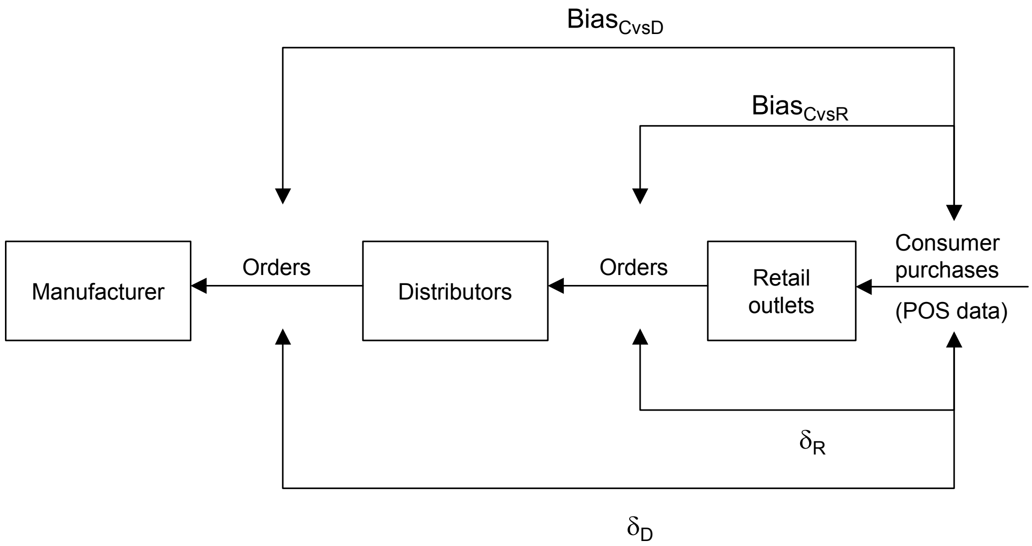

Figure 9. Measuring the variability and bias of the different types of sales data.

In practice, the actual magnitude of the bias after the transient phase is of little interest to production and inventory control. What is more important is to know when the transient phase is over and when order data starts to reflect consumer purchases reasonably accurately. A practical issue encountered when examining the data was defining exactly when the product introduction period ends. The solution adopted was to calculate how many days it takes for the bias to reach 90% - 110% of the average bias for the remaining period. In practice, this was found to approximately indicate the point in time when both distributor orders and demand at the retail outlets reach a stationary state. This measure, called the delay in demand synchronization, is the third measure used in this study and indicates how long it takes for sales data at the different echelons of the supply chain to start portraying demand in a similar way. Two measures of delay in demand synchronization (DDS) are used. We measure how long it takes before the retail outlets' orders to the distributors are synchronized with sales to consumers (DDS_{CvsR}), and how long it takes until the distributors' orders to the manufacturer are synchronized with sales to consumers (DDS_{CvsD}). Since the bias values tend to fluctuate quite much when batch sizes are large, a five-period moving average of $Bias_{CvsR}$ is used when calculating the DDS_{CvsR} and a ten-period moving average of $Bias_{CvsD}$ is used when calculating the DDS_{CvsD}.

As the inventory parameters in the simulation model are set so that neither the distributors' inventories nor the manufacturer's finished goods inventory face stock-outs, the metrics of inventory turn, fill-rate, availability, or backlog do not differentiate between the scenarios of information sharing or no information sharing. Instead, a measure called the potential minimum average inventory is used in this study to evaluate operational efficiency. This measure illustrates how low the inventory level could have been without causing stock-outs.

4.2.3 Results

Bias and delay in demand synchronization at the retail outlets

When looking at the bias and delay in demand synchronization induced by the retail outlets, notable differences between the seventeen product introductions can be observed. The development of the retail bias over time for the situation of the retail outlets' inventories being initialized to one full wholesale package above the re-order point is shown in Figure 10. To illustrate the trend more clearly, a seven-day moving average of the bias is used to filter out day-to-day variation.

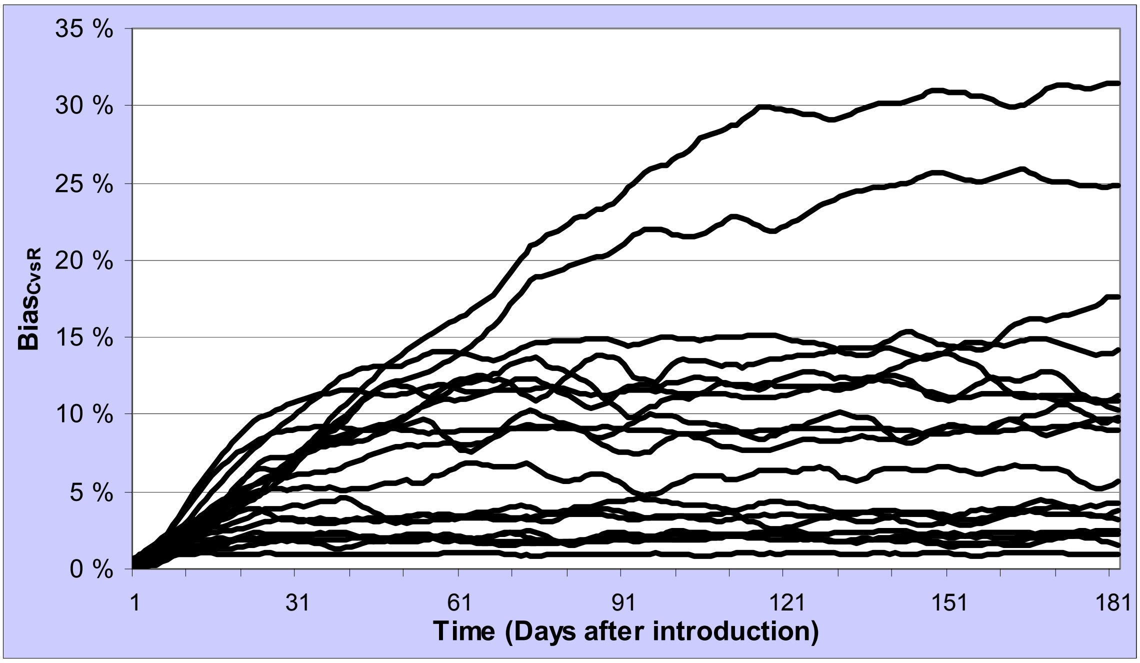

Figure 10. Retail bias ($Bias_{CvsR}$) as a function of time. (Each line represents a product. Inventories at the retail outlets are initialized to one wholesale package above the re-order point.)

Both the magnitude of the bias as well as the time it takes until it begins to level out, i.e. for the transient phase to end, are quite different for the different products. For some products, it takes less than two weeks before the orders placed by the retail outlets start to accurately reflect consumer demand. For other products, the bias induced by the retail outlets increases over a long period of time. Even after 120 days, in the most extreme case, consumer demand and the retail outlets' orders are not in balance and bias is still increasing. However, all products reach a stationary state during the simulation period of 182 days when examining the $Bias_{CvsR}$ metric.

When further examining the simulation results, a clear relationship between the products' retail biases and the size of their wholesale packages, measured in days of supply at the retail outlets emerges (see Figure 11). The R^2 value of the correlation for the seventeen product introductions is 0,992. This means that $Bias_{CvsR}$ is almost perfectly explained by the size of a product's wholesale package compared with its average sales per retail outlet.

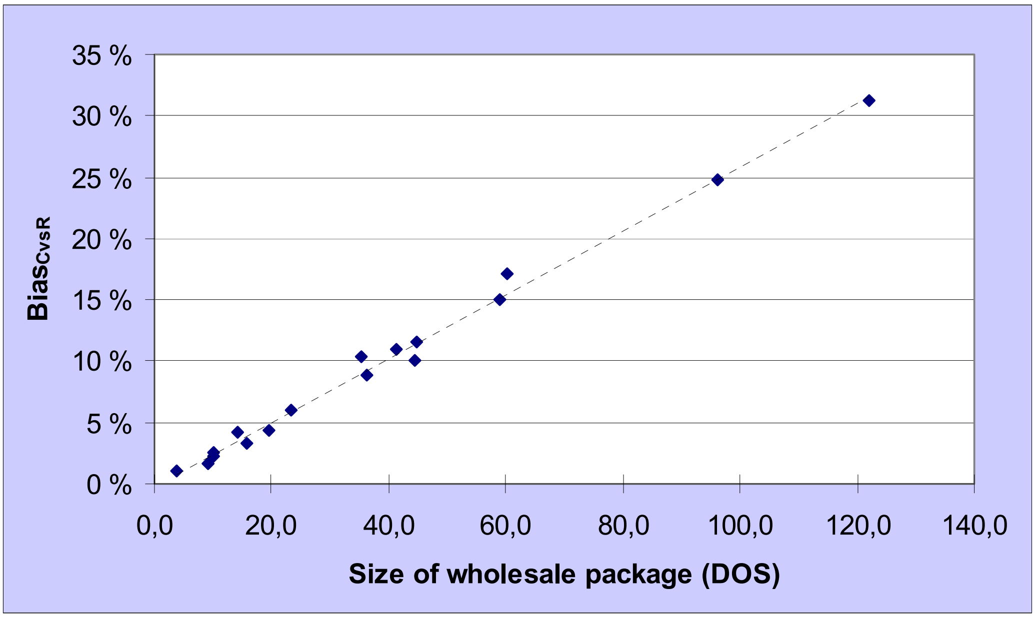

Figure 11. Retail bias as a function of the size of the products' wholesale packages. (Each dot represents a product. Inventories at the retail outlets are initialized to one wholesale package above the re-order point.)

The result is logical. Since all of the retail outlets are initially stocked with a full wholesale package above the re-order point, orders to the distributors are never placed until the outlets have sold an entire wholesale package of goods. Orders to the distributors, thus, constantly lag behind sales to consumers (see Figure 12).

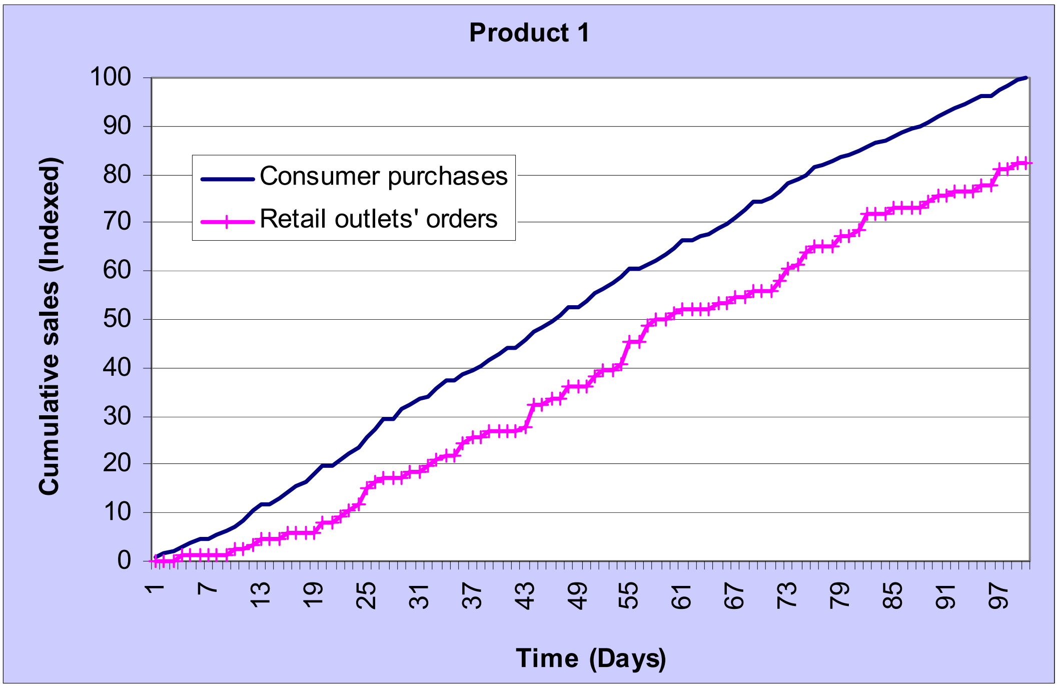

Figure 12. Cumulative consumer purchases and orders placed by the retail outlets for an example product (Inventories at the retail outlets are initialized to one wholesale package above the re-order point.)

This also means that there is a relationship between the size of a product's wholesale package and the delay in demand synchronization induced by the retail outlets. This is illustrated in Figure 13. The correlation value R^2 is 0,915, i.e. the size of the wholesale package explains the delay in demand synchronization quite well.

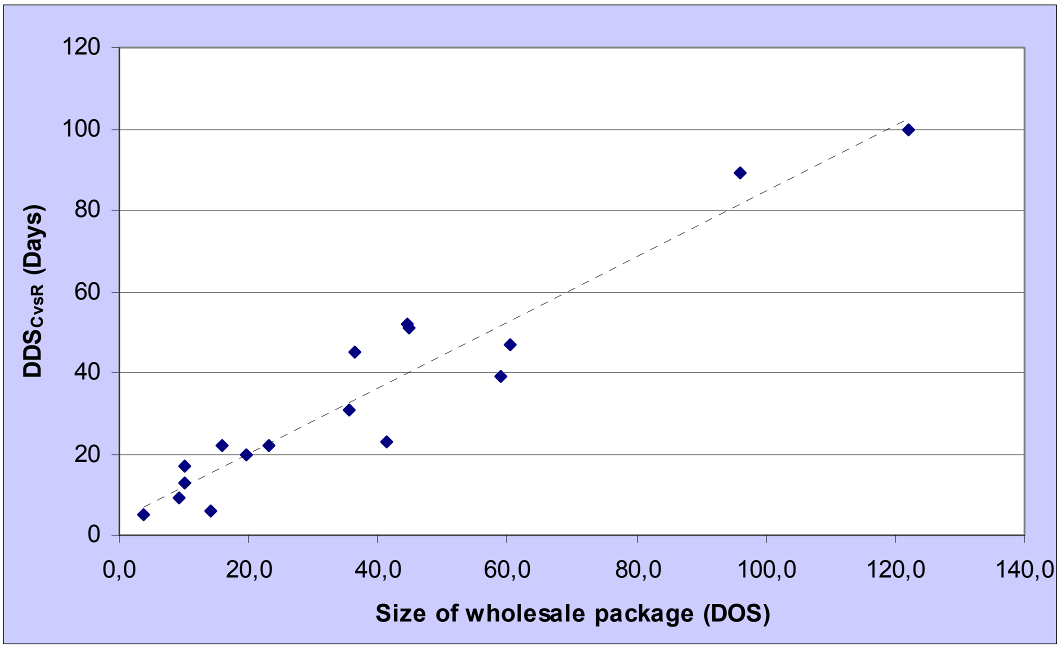

Figure 13. Delay in demand synchronization at the retail outlets as a function of the size of the products' wholesale packages. (Each dot represents a product. Inventories at the retail outlets are initialized to one wholesale package above the re-order point.)

Of course, the retail outlets' inventories do not necessarily need to be initialized to a full wholesale package above the re-order point. Therefore, it is interesting to examine what happens when the level of initial inventory is changed. As illustrated by Table 8, the initial inventories at the retail outlets have a notable impact on the resulting retail bias. When the inventories are initialized to half a wholesale package above the re-order point, the resulting retail bias is, on average, 111% lower than when they are initialized to a full wholesale package above the re-order point. When the inventories are initialized to one third of a wholesale package above the re-order point, the retail bias is, on average 155% lower than in the base case.

Table 8. Retail bias for different levels of initial inventory at the retail outlets.

	$Bias_{CvsR}$ for different levels of initial inventory		
	ROP + 1 WP	**ROP + 1/2 WP**	**ROP + 1/3 WP**
Product 1	10,4 %	-0,6 %	-3,9 %
Product 2	6,0 %	0,1 %	-1,6 %
Product 3	2,5 %	-0,4 %	-1,3 %
Product 4	3,3 %	-0,6 %	-2,0 %
Product 5	11,0 %	0,1 %	-3,7 %
Product 6	1,1 %	0,1 %	-0,6 %
Product 7	2,2 %	-0,8 %	-1,9 %
Product 8	10,0 %	0,1 %	-2,7 %
Product 9	17,1 %	-3,3 %	-7,1 %
Product 10	4,2 %	0,0 %	-2,4 %
Product 11	24,8 %	-2,8 %	-9,4 %
Product 12	31,2 %	-1,6 %	-12,7 %
Product 13	11,6 %	0,2 %	-3,8 %
Product 14	15,0 %	-1,2 %	-6,9 %
Product 15	8,9 %	-0,4 %	-5,1 %
Product 16	4,4 %	-2,4 %	-3,7 %
Product 17	1,6 %	-0,3 %	-2,5 %
Average	*10,0 %*	*-1,0 %*	*-4,0 %*

ROP = re-order point, WP = wholesale package

Again, there is a correlation between the size of a product's wholesale package and the amount of bias induced by the retail outlets. This is illustrated in Figure 14. For the situation of the retail outlets initially being stocked with a full wholesale package above the re-order point, the correlation value R^2 is 0,992. For the situation of the retail outlets being stocked with half a wholesale package above the re-order point, R^2 is 0,277. Finally, for the situation of the retail outlets being stocked with an initial inventory of one third of a wholesale package above the re-order point, R^2 is 0,918. The poor explanatory power of the size of the products' wholesale packages in the second situation is probably due to large percentual fluctuations in bias caused by its small value.

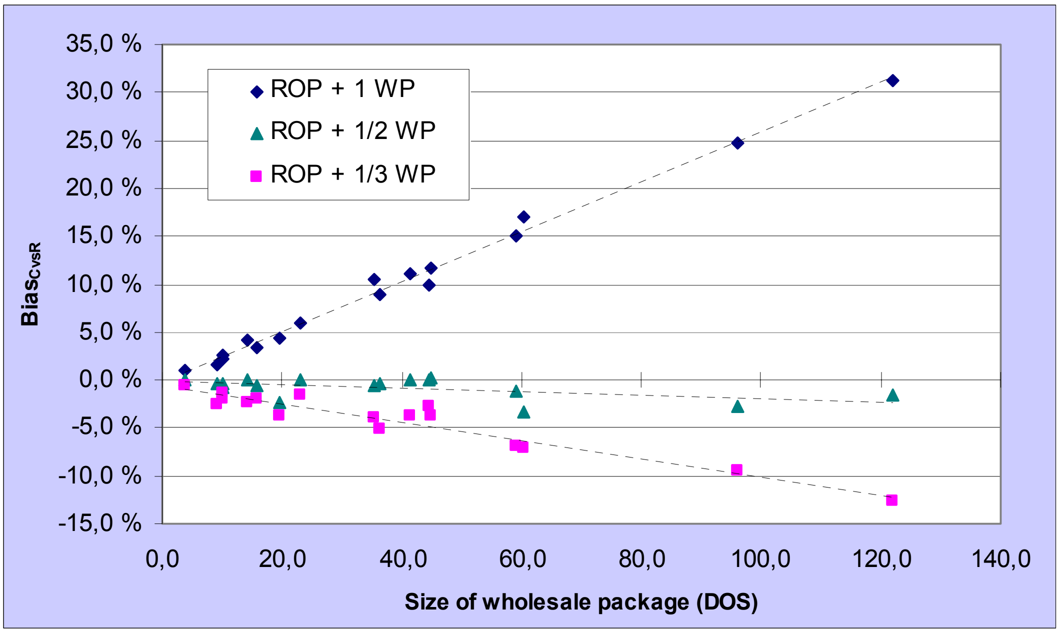

Figure 14. Retail bias as a function of the products' wholesale package sizes for three different levels of initial inventory at the retail outlets.

Interestingly, it seems that by setting the initial inventory to a value close to half a wholesale package above the re-order point, the retail bias can be almost eliminated. This is further illustrated for an example product in Figure 15.

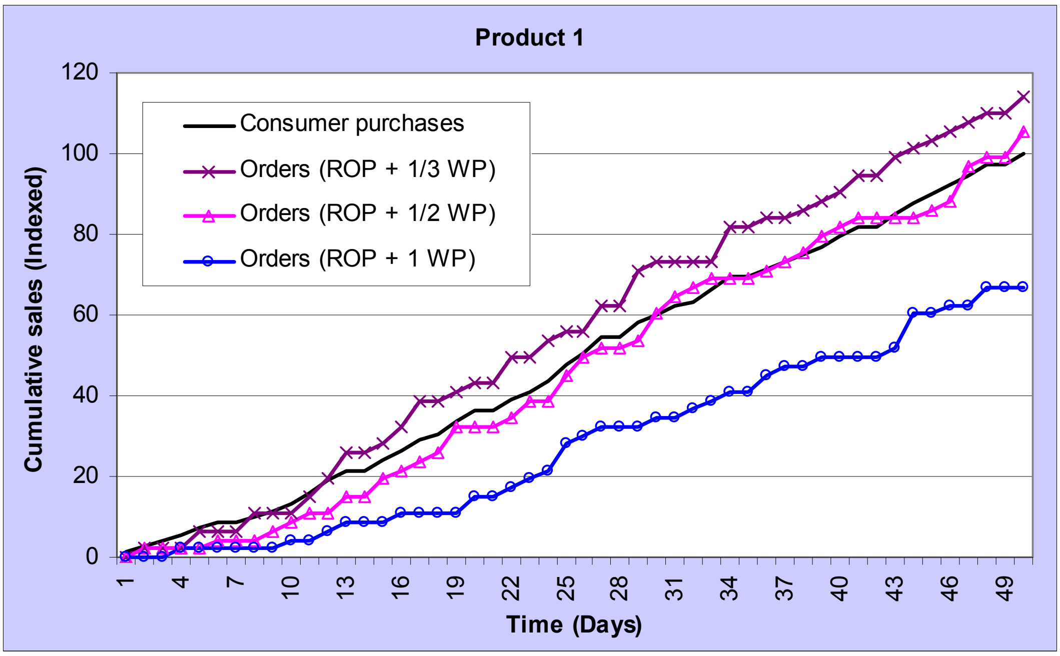

Figure 15. Cumulative consumer purchases and orders placed by the retail outlets for an example product for different levels of initial inventory at the retail outlets.

When examining the impact of initial inventory levels on the delay in demand synchronization, the results are different (see Table 9). Although, on average, a reduction in initial inventory at the retail outlets reduces the delay in demand synchronization, this reduction is smaller than the reduction in retail bias. When the inventories are initialized to half a wholesale package above the re-order point, the resulting delay in demand synchronization is, on average, 12% lower than when they are initialized to a full wholesale package above the re-order point. When the inventories are initialized to one third of a wholesale package above the re-order point, the delay in demand synchronization is, on average, 19% lower than in the base case. However, as the bias values in the case of initial inventories being set to half a wholesale package above the re-order point are extremely small, the delay measurements are somewhat unreliable. Even very small changes in the bias appear in the examination as extremely large percentual fluctuations, making it difficult to attain reliable readings.

Table 9. Delay in demand synchronization at the retail echelon for different levels of initial inventory at the retail outlets.

	DDS_{CvsR} for different levels of initial inventory		
	ROP + 1 WP	**ROP + 1/2 WP**	**ROP + 1/3 WP**
Product 1	31	30	22
Product 2	22	18	17
Product 3	17	5	13
Product 4	22	21	16
Product 5	23	22	18
Product 6	5	3	3
Product 7	13	8	6
Product 8	52	14	43
Product 9	47	42	39
Product 10	6	7	5
Product 11	89	142	107
Product 12	100	16	95
Product 13	51	51	41
Product 14	39	54	32
Product 15	45	28	20
Product 16	20	32	9
Product 19	9	9	16
Average	*35*	*30*	*30*

ROP = re-order point, WP = wholesale package

Again, there is a correlation between the size of a product's wholesale package and the delay in demand synchronization induced by the retail outlets. This is illustrated in Figure

16. For the situation of the retail outlets being stocked with an initial inventory of one wholesale package above the re-order point, the value R^2 equals 0,915. For the situation of the retail outlets being stocked with an initial inventory of half a wholesale package above the re-order point, the correlation value R^2 equals 0,338. Finally, for the situation of the retail outlets being stocked with an initial inventory of one wholesale package above the re-order point, the correlation value R^2 is 0,873. The poor explanatory power of the size of the products' wholesale packages in the second case is, again, probably due to large percentual fluctuations in bias, which make accurate estimation of the delay in demand synchronization difficult.

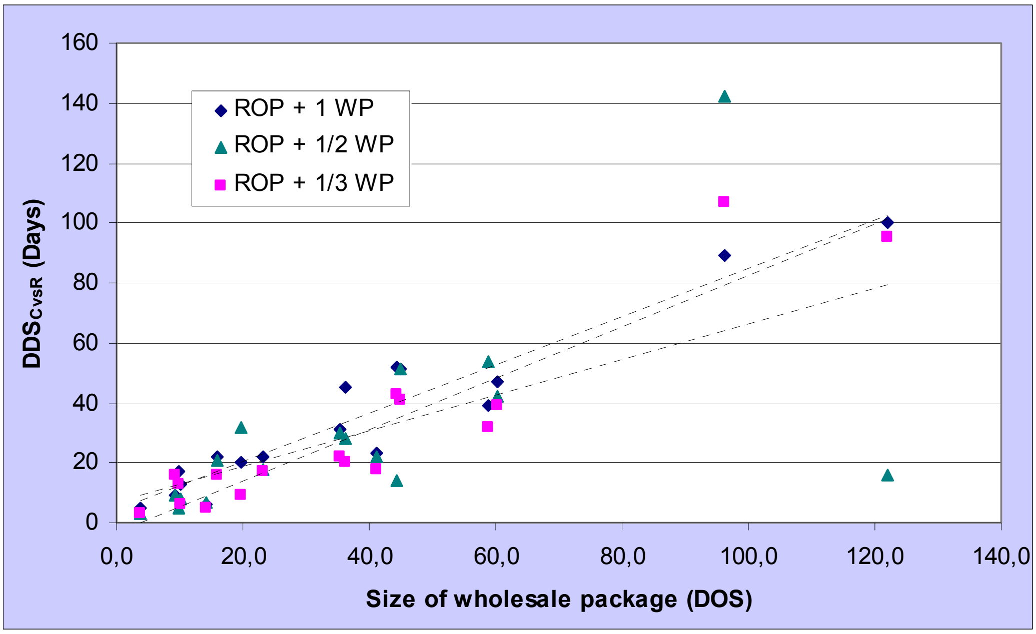

Figure 16. Delay in demand synchronization at the retail echelon as a function of the products' wholesale package sizes for different levels of initial inventory at the retail outlets. (Each dot represents a product)

Bias and delay in demand synchronization at the distributors

We also compare distributor orders to the manufacturer with consumer purchases at the retail outlets to establish the total bias and total delay in demand synchronization in the examined supply chain. Again, there are very large differences between the products, both when looking at the absolute bias and delay values and when looking at the increase or decrease in these values compared with the results attained for the retail echelon.

The results for the bias examination are presented in Table 10 (for the situation where the retail outlets' inventories are initialized to one wholesale package above the re-order point) and Table 11 (for the situation where the retail outlets inventories are initialized to a third of a wholesale package above the re-order point). Quite logically, and similarly to the results for the retail echelon, a higher amount of initial stock at the distributors corresponds with a higher level of total bias.

Table 10. Retail bias and total bias for two levels of initial inventory at the distributors. (The retail outlets' inventories are initialized to one wholesale package above the re-order point).

	$Bias_{CvsR}$	$Bias_{CvsD}$	
	ROP + 1 WP	**ROP + 1 DB**	**ROP + 1/3 DB**
Product 1	10,4 %	13,4 %	9,1 %
Product 2	6,0 %	9,3 %	6,4 %
Product 3	2,5 %	26,2 %	1,6 %
Product 4	3,3 %	13,4 %	4,8 %
Product 5	11,0 %	16,4 %	11,5 %
Product 6	1,1 %	3,9 %	0,5 %
Product 7	2,2 %	4,0 %	2,3 %
Product 8	10,0 %	20,7 %	-2,0 %
Product 9	17,1 %	59,2 %	18,4 %
Product 10	4,2 %	5,1 %	5,1 %
Product 11	24,8 %	41,3 %	21,8 %
Product 12	31,2 %	58,8 %	26,1 %
Product 13	11,6 %	19,9 %	19,9 %
Product 14	15,0 %	37,6 %	6,4 %
Product 15	8,9 %	13,5 %	13,5 %
Product 16	4,4 %	6,2 %	6,2 %
Product 17	1,6 %	8,0 %	5,0 %
Average	*9,7 %*	*21,0 %*	*9,2 %*

ROP = re-order point, WP = wholesale package, DB = distribution batch

Table 11. Retail bias and total bias for two levels of initial inventory at the distributors. (The retail outlets' inventories are initialized to one third of a wholesale package above the re-order point).

	$Bias_{CvsR}$	$Bias_{CvsD}$	
	ROP + 1/3 WP	ROP + 1 DB	ROP + 1/3 DB
Product 1	-4 %	0 %	-4 %
Product 2	-2 %	1 %	-5 %
Product 3	-1 %	2 %	2 %
Product 4	-2 %	13 %	-4 %
Product 5	-4 %	7 %	-8 %
Product 6	-1 %	4 %	-3 %
Product 7	-2 %	1 %	-3 %
Product 8	-3 %	9 %	-2 %
Product 9	-7 %	18 %	-22 %
Product 10	-2 %	1 %	-4 %
Product 11	-9 %	2 %	-17 %
Product 12	-13 %	1 %	-11 %
Product 13	-4 %	20 %	-34 %
Product 14	-7 %	22 %	-9 %
Product 15	-5 %	14 %	-15 %
Product 16	-4 %	-1 %	-8 %
Product 17	-3 %	5 %	1 %
Average	*-4,2 %*	*7,0 %*	*-8,7 %*

ROP = re-order point, WP = wholesale package, DB = distribution batch

However, whereas the bias induced by the retail echelon can be directly linked to the size of a product's wholesale package, no such obvious relationship can be found between the total bias and the level of batching in the supply chain.

Table 12. R^2 values attained for polynomials of different form with parameters selected for best fit with observed values of total bias for different inventory initializations.

	ROP+1 WP ROP+1 DB	ROP+1 WP ROP+1/3 DB	ROP+1/3 WP ROP+1 DB	ROP+1/3 WP ROP+1 DB
$\alpha DB+C$	0,403	0,330	0,636	0,683
$\alpha WP+C$	0,694	0,604	0,391	0,640
$\alpha(WP+DB)+C$	0,716	0,666	0,028	0,247
$\alpha WP+\beta DB+C$	0,784	0,709	0,695	0,696
$\alpha WP+\beta DB^2+C$	0,780	0,747	0,599	0,787
$\alpha WP^2+\beta DB+C$	0,798	0,719	0,718	0,692

ROP = re-order point, WP = wholesale package, DB = distribution batch

In order to establish whether a polynomial equation could be used to describe the relationship between the batch sizes and total bias, the least squared error method was used to find the parameter settings for several equations that produced the best fit with the bias values attained in the simulations. The equations and their R^2 values when compared with the bias data are presented in Table 12. The results are inconclusive: several polynomials produce similar results.

The results for the delay in demand synchronization examination are presented in Table 13 (for the situation where the retail outlets' inventories are initialized to one wholesale package above the re-order point) and Table 14 (for the situation where the retail outlets inventories are initialized to a third of a wholesale package above the re-order point).

Table 13. Delay in demand synchronization at the retail echelon and total delay in demand synchronization for two levels of initial inventory at the distributors. (The retail outlets' inventories are initialized to one wholesale package above the re-order point).

	DDS_{CvsR}	DDS_{CvsD}	
	ROP + 1 WP	ROP + 1 DB	ROP + 1/3 DB
Product 1	31	51	37
Product 2	22	58	20
Product 3	17	53	47
Product 4	22	41	40
Product 5	23	33	29
Product 6	5	33	12
Product 7	13	25	8
Product 8	52	72	47
Product 9	47	74	23
Product 10	6	14	17
Product 11	89	98	106
Product 12	100	93	105
Product 13	51	114	52
Product 14	39	113	64
Product 15	45	128	61
Product 16	20	24	25
Product 17	9	15	25
Average	*35*	*61*	*42*

ROP = re-order point, WP = wholesale package, DB = distribution batch

Table 14. Delay in demand synchronization at the retail echelon and total delay in demand synchronization for two levels of initial inventory at the distributors. (The retail outlets' inventories are initialized to one third of a wholesale package above the re-order point).

	DDS_{CvsR}	DDS_{CvsD}	
	ROP + 1 WP	ROP + 1 DB	ROP + 1/3 DB
Product 1	22	22	22
Product 2	17	9	17
Product 3	13	49	13
Product 4	16	35	16
Product 5	18	24	18
Product 6	3	22	3
Product 7	6	25	6
Product 8	43	38	43
Product 9	39	66	39
Product 10	5	10	5
Product 11	107	82	107
Product 12	95	80	95
Product 13	41	88	41
Product 14	32	55	32
Product 15	20	98	20
Product 16	9	16	9
Product 17	16	6	16
Average	*30*	*43*	*30*

ROP = re-order point, WP = wholesale package, DB = distribution batch

Again, the results are similar to the results attained for the retail echelon; the amount of initial inventory at the distributors has an impact on the increase in delay, but the impact is smaller than on the increase in bias. Interestingly, when the distributors' inventories are initialized to one distribution batch above the re-order point, the average increase in delay is 120% for both initializations (one wholesale package above the re-order point and a third of a wholesale package above the re-order point) of inventory levels at the retail outlets. However, when the distributor inventories are initialized to one third of a distribution batch over the re-order point, the result is an average increase in delay of 50% when retail outlets are initialized to the higher stock level and an average reduction of 18% when the retail outlets are initialized to the lower stock level.

Although larger batch sizes seem to correlate with larger delays, no clear relationship between the size of a product's wholesale package or the size of its distribution batch and the total delay in demand synchronization could be identified. The least squared error approach was used to find the best fitting parameters for a number of different polynomial equations. Next, the fit between these equations and the attained delay values was examined. The results were, again, inconclusive: several of the equations produce similar results. The tested equations and the R^2 values attained are presented in Table 15.

Table 15. R^2 values attained for polynomials of different form with parameters selected for best fit with observed values for total delay in demand synchronization for different inventory initializations.

	ROP+1 WP ROP+1 DB	ROP+1 WP ROP+1/3 DB	ROP+1/3 WP ROP+1 DB	ROP+1/3 WP ROP+1 DB
αDB+C	0,631	0,152	0,686	0,387
αWP+C	0,717	0,446	0,776	0,616
α(WP+DB)+C	0,415	0,724	0,443	0,580
αWP+βDB+C	0,720	0,724	0,780	0,666
αWP+βDB^2+C	0,625	0,736	0,697	0,659
αWP^2+βDB+C	0,701	0,722	0,801	0,703

ROP = re-order point, WP = wholesale package, DB = distribution batch

Variability

Increase in demand variability when moving upstream in a supply chain is the most commonly used measure of the bullwhip effect. We examined the variability of the retail outlets' orders to the distributors as well as the distributors' orders to the manufacturer. The results are presented in Table 16 (results for only one initialization of inventories are presented here as there are only marginal differences between the results for the different scenarios). The increase in variability caused by the distributor echelon is typically large. Only for one of the products, Product 1, is the increase in variability less than 200%. The average increase is as much as 436%.

Table 16. Variability results for the examined product introductions. (Inventory at the retail outlets is initialized to one wholesale package above the re-order point; inventory at the distributors is initialized to the re-order point rounded up to the nearest multiple of the distribution batch size.)

	δ_R	δ_D	$\Delta\delta_{D/R}$
Product 1	46	82	79 %
Product 2	59	103	76 %
Product 3	16	244	1415 %
Product 4	38	381	916 %
Product 5	1 528	4 866	218 %
Product 6	89	714	702 %
Product 7	19	61	219 %
Product 8	85	526	516 %
Product 9	28	161	466 %
Product 10	65	160	148 %
Product 11	60	272	350 %
Product 12	56	228	307 %
Product 13	99	622	527 %
Product 14	76	509	573 %
Product 15	34	340	903 %
Product 16	6	30	388 %
Product 17	9	34	270 %
Average	*214*	*626*	*436 %*

Impact of information sharing on manufacturer's production and inventory control

In the simulation model, the manufacturer makes use of its access to downstream sales data by directly its production with aggregate POS data rather than with distributor orders. Since the inventory control parameters in the model are set to ensure that there are no stock-outs, the retail outlets' or distributors' inventory levels are not affected by which kind of demand information, POS data or distributors' orders, is used to load production. Information sharing only affects the manufacturer's production load and the manufacturer's finished goods inventory.

Based on the previous results indicating a delay in demand synchronization between orders at the different echelons of the supply chain and consumer purchases, one could assume that a manufacturer could attain benefits in its production and inventory control by using downstream sales data to control these functions. Table 17 demonstrates the actual impact of using POS data for production loading on the manufacturer's finished goods inventory expressed in days of supply (DOS). The inventory is the potential minimum average inventory. As can be seen from the table, there is no obvious beneficial impact of information sharing on the manufacturer's finished goods inventory. For ten products, inventory decreases, but for seven it increases as a result of loading production with POS data rather than with distributor orders.

Table 17. Manufacturer's finished goods inventory without and with information sharing.

	Inventory without information sharing (DOS)	Inventory with information sharing (DOS)	Difference
Product 12	26,3	53,0	50 %
Product 7	9,7	12,3	21 %
Product 10	16,2	17,8	9 %
Product 17	14,5	15,4	6 %
Product 4	22,8	24,0	5 %
Product 8	36,5	37,1	2 %
Product 6	28,4	28,6	1 %
Product 1	16,5	16,4	-1 %
Product 2	17,2	16,2	-6 %
Product 11	35,4	32,1	-10 %
Product 3	35,1	31,5	-11 %
Product 16	18,5	14,9	-24 %
Product 15	51,0	40,3	-27 %
Product 13	51,7	36,9	-40 %
Product 9	172,1	109,2	-58 %
Product 14	62,9	39,8	-58 %
Product 5	30,4	17,6	-73 %

The reason for this somewhat surprising result is that when the manufacturer tries to benefit from the information sharing by loading its production with aggregate POS data, its production starts to reflect sales at the retail outlets. If the distributors' orders to the manufacturer lag behind sales at the retail outlets (i.e. there is a positive bias), the manufacturer's finished goods inventory grows as goods are produced in anticipation of distributor orders. This effect could be managed by taking into account the bias and delay in demand synchronization when loading production. However, this would require the manufacturer to be able accurately estimate the delay in advance, which is not straightforward and was not implemented in the simulation model presented here.

It is important to keep in mind that all inventories in the model have been set high enough so that no stock-outs occur and that actual inventory levels are not used as a performance measure. In reality, the original inventory parameters could be set too low or too high, and one way of using the downstream data would be to make accurate forecast updates, i.e. to update inventory parameters more rapidly. Similarly, access to downstream sales data could be used for synchronizing purchasing of raw materials with consumer sales to reduce the risk of purchasing too much or too little in the critical first months of a product introduction.

4.2.4 Conclusions

The results of this study clearly demonstrate how, for recently introduced products, the different echelons of a supply chain induce bias and delay to the demand signal passing through them. In some cases the distortion is very large; the highest delay values encountered in the sample of seventeen products examined were over 100 days and the highest bias values over 50% of total sales. However, in some cases the distortion is barely noticeable; the sample included situations of almost zero bias and products with delays of less than 10 days.

The results of the study indicate that the bias and delay induced by the retail echelon are related to the amount of batching, i.e. the size of a product's wholesale package in relation to its average sales per retail outlet. The initial level of inventory at the retail outlets also has an impact, especially on the bias; higher inventory means more bias and larger delays, while an optimal initial inventory level may eliminate the bias and decrease the delay in demand synchronization. At the distributor echelon these same general principles seem to apply, although the relationships are more complex. More research is needed to identify the exact form of the relationship between bias and delay in demand synchronization and the batch sizes at the retail outlets and the distributors.

In relation to Question 1 concerning the situations in which access to downstream demand information is most valuable, Study 2 thus indicates that information sharing is especially valuable for products with high amounts of batching in the supply chain. Order batching has already previously been shown to be a key factor causing increase in demand variability in supply chains (see Study 1 and Kaipia et al., 2002). This study shows that order batching is an important factor explaining bias and delay in demand synchronization, as well. Furthermore, the results indicate that the initial inventory at the nodes in a supply chain, another form of batching, plays an important role in the formation of bias and delay.

Fransoo and Wouters (2000) point out that the different echelons of a supply chain may have a different impact on the increase in demand variability. Study 2 continues this discussion. The results of the study indicate that variability, bias, and delay can be induced by different echelons of the supply chain and that these effects do not necessarily appear in the same situations or at the same echelons. For all but one of the products in the sample, the distribution echelon was the main source of variability. Yet, for many of the products and especially for certain inventory initializations, the main source of delay and bias was the retail echelon. This indicates that although one can argue that POS data is always the best option, as suggested by Kiely (1998), depending on the product and the purpose of the information-sharing effort (to reduce variability or to remove delay or bias), there may or may not be a big difference between POS and sell-through data. In practice, manufacturer access to distributor sell-through may not have a very large impact on how rapidly the manufacturer is able to synchronize its operations with consumer sales. However, sell-through data may still be beneficial to the manufacturer as it removes the often-notable variability increase in demand caused by the distributor echelon, as shown by Study 1.

Since the increase in variability and the increase in delay are not necessarily linked, as shown by Study 2, the traditional means of measuring the bullwhip effect by comparing demand variability at different stages of a supply chain only gives a limited picture of the demand signal distortion that takes place. The bias and delay in demand synchronization measures introduced in this study are a first attempt at capturing these effects. However, additional research is needed to confirm the validity of these measures and to further develop them for increased accuracy.

In relation to Question 2 concerning to the prerequisites for manufacturers to be able to benefit from access to downstream sales data, Study 2 shows how simply loading the manufacturer's production with POS data can, in fact, increase the manufacturer's inventories. In order to get a more realistic picture of the usefulness of POS data in managing product introductions, forecasting needs to included in the model. In the model used in Study 2, a perfect forecast is implicitly assumed as inventory re-order points are set so that no stock-outs occur. In addition, the model does not include purchasing of raw or packaging materials or capacity constraints that would require the manufacturer to forecast demand. More research is needed to assess the usefulness of POS data in updating forecasts for new products.

4.3 Value of manufacturer access to POS data in product introductions (Study 3)*

4.3.1 Purpose of the study

Study 3 continues where Study 2 ended by using a case study approach to empirically examine how manufacturers are able to use POS data to update forecasts for recently introduced products. Study 3 provides answers to Question 1: In what situations does sharing of downstream demand information with upstream supply chain members enable increased efficiency? and especially to Question 2: What are the prerequisites for upstream supply chain members to be able to benefit from access to downstream sales data?

The inspiration for this study came from the work of Fisher and Raman (1996) on the use of early order data in estimating total product sales. Fisher and Raman (ibid.) present a method for estimating the demand distributions of new products, for incorporating information on early sales into the planning process, and for making production decisions before and during the season. They examine seasonal products that are sold at a discount when the season is over. In their supply chain setting, production decisions are made only twice: first before the beginning of the sales season and then a second time during the season after receiving initial orders.

In Study 3, the research setting is, however, somewhat different. The focus is on recently introduced consumer goods with longer life cycles but unknown demand. The objective of the study is to examine how manufacturer's can use POS data on early sales in controlling production, inventory levels and purchasing of raw materials for new products, i.e. not just to make decisions concerning the production quantity. The study aims to identify the attainable benefits as well as contingency factors potentially having an impact on the value of information sharing.

4.3.2 Methodology

In Study 3, an case study approach was selected in order to overcome the problems related to modeling complex situations. Rather than trying to model how POS data could be shared and used, a pilot implementation was designed based on results of data analyses. The pilot and subsequent process implementation made it possible to observe how actual companies engage in information sharing and what benefits they attain and what problems they face.

*Results from this study have previously been presented in Småros, J. (2004), "The value of point-of-sales data in managing product introductions: Results from a case study", Proceedings of the 16th annual NOFOMA Conference, pp. 617-630.

Case selection

Study 3 involves four companies operating in the grocery sector: a retailer, a logistics and purchasing company, and two manufacturers.

The retailer, here called RetailCo, operates in Northern Europe and is considered progressive in the area of logistics. It has been involved in several of ECR Europe's development projects and sees efficient logistics as a source of competitive advantage. For the company, openness and close relationships with its suppliers form an important part of its business strategy. Consequently, the retailer has recently decided to give manufacturers access to its POS data, provided that the information sharing can be shown to result in efficiency improvements in the supply chain.

A large proportion of RetailCo's goods are purchased and distributed by a logistics company jointly owned by RetailCo and one of its competitors. The logistics company is also included in the study, although not as a principal actor.

The two manufacturers examined in the study, CandyCo and ChemCo, were selected based on their involvement in the information-sharing project with RetailCo. From RetailCo's point of view, testing the potential benefits of providing manufacturer access to POS data first with these two manufacturers was a logical step. The retailer and the manufacturers have a good relationship and have also previously been involved in joint development efforts. Both of the manufacturers, for example, have VMI arrangements with RetailCo's logistics company.

Although manufacturer selection was based on RetailCo's preferences rather than theoretical sampling, the two manufacturers nevertheless enable interesting comparisons from a research point of view. Both companies are producers of consumer packaged goods; CandyCo of confectionery products with limited shelf life and ChemCo of personal hygiene and household cleaning products with virtually unlimited shelf life. In addition, ChemCo is a large multinational company with specialized production plants serving global markets. CandyCo is an international, but significantly smaller company. The country in which the case study was carried out is CandyCo's home market and some of the company's main production facilities are located there. To ChemCo, the country represents only one market among several others.

Data collection and analysis

The research included three phases. In the first phase, historical POS data on product introductions was analyzed in order to better understand its potential usefulness in updating forecasts for recently introduced products. The analyzed sample included a total of 109 products introduced during the first half of 2002 and belonging to three different product categories: CandyCo's main product category and two of ChemCo's most important product categories. In order to attain a sufficient sample size, both the case manufacturers' and their competitors' products were examined. The sample also included several different kinds of product introductions: true novelties, line extensions, and new versions of existing products. Information on the nature of the product introductions was received from the manufacturers' key account managers and the retailer's category managers. The data consisted of daily product and chain level sales for time periods ranging from a little less than three months to over six months following the products' introductions. The first phase of the research included graphical examination of the products' sales profiles, scatter plots of the relationship between early POS data and the products' later sales, as well as correlation studies. The results of the data analyses were discussed with company representatives and used when designing a pilot implementation. The author's role in designing the pilot implementation was to make recommendations, based on the data analyses, concerning how information should be shared and how it should be interpreted in the pilot implementation.

The second phase of the research consisted of the pilot implementation in which sharing of POS data for recently introduced products was tested in practice. The pilot was conducted in the fall of 2002. It included all nine of CandyCo's product introductions in RetailCo's chains in September 2002, representing both high- and low-volume products, as well as line extensions and a few true novelties. Seven of ChemCo's new product introductions in two categories were selected for examination by company representatives to ensure that products with different sales patterns and volumes were included. ChemCo's sample did, however, not include any true novelties, just line extensions. Information on the products was attained from the two companies' key account managers. During the pilot, the author participated in the manufacturers' forecasting meetings to monitor how the POS data was used and what kind of forecast updates its use resulted in. After the pilot, interviews with the manufacturers' key account managers and with RetailCo's logistics planners involved in the pilot were conducted.

In the beginning of 2003, RetailCo and the two manufacturers decided to continue their co-operation on a permanent basis. The information-sharing approach piloted in the fall of 2002 was slightly modified and integrated into the companies' processes for managing product introductions. In the fall of 2003, data on CandyCo's forecast accuracy and customer service levels before and after the beginning of the information-sharing co-operation with the retailer were compared. Corresponding data from ChemCo was not available due to problems with the company's enterprise resource planning system. Instead, an interview with ChemCo's logistics manager was conducted.

Table 18. The three phases of the research conducted in Study 3.

Phase	Content	Data sources used in the research
Phase I	Data analyses of historical product introductions	▪ POS data on 109 product introductions ▪ Discussions with the manufacturers' key account managers
Phase II	Pilot implementation	▪ Monitoring of use of POS data for seven of ChemCo's introductions and nine of CandyCo's introductions ▪ Interviews with the manufacturers' key account managers and RetailCo's logistics planners
Phase III	Permanent process	▪ Forecast accuracy and service level data from CandyCo's enterprise resource planning system ▪ Interview with ChemCo's logistics manager

It is important to notice that the role of the author in this study was more active than is typical in case research. To tackle the potential problem of researcher bias, the companies' and the author's different roles were defined in the beginning of the study and emphasized throughout the study. The author's role was to support the development process by providing data analyses, acting as a neutral referee ensuring that all parties' viewpoints were considered, and by acting as an unbiased observer when examining the impact of the information-sharing pilot and the subsequent process implementation. The companies' role was to make decisions concerning what ideas to implement, what information to share, and how the information-sharing process should be set up in practice.

4.3.3 Results of initial data analyses

The co-operation between RetailCo and the manufacturers began with RetailCo expressing its willingness to share POS data with manufacturers, provided that this would bring about an increase in supply chain efficiency. RetailCo first approached ChemCo to discuss different opportunities to use POS data upstream in the supply chain. The companies agreed to start by examining whether POS data could be of value in updating ChemCo's forecasts for recently introduced products. The idea was that by giving ChemCo access to POS data, the manufacturer would be able to correct forecast errors more rapidly than by monitoring order data or syndicated demand data. Another company, CandyCo was also included in the development project to broaden the view and to include products of a somewhat different nature in the examination.

In order to get more information on the potential usefulness of POS data in managing product introductions, a sample of 38 recent product introductions in two of ChemCo's product categories and 71 product introductions in CandyCo's main product category was analyzed.

Although there were some surprises in the products' demand patterns, a graphical examination indicated that the products' sales typically evolved in a rather logical manner. When discussing the products' sales profiles with ChemCo's and CandyCo's key account managers, the following observations were made:

- Most products' sales volumes seem to grow steadily until reaching something of a plateau, i.e. level sales.
- Rapid changes or peaks in demand are typically caused by promotions.
- For many products demand stabilizes within 25 to 30 days following their introduction, but for some products demand continues to grow even after 60 days or more.
- The sales of true novelties typically grow for a longer period of time than the sales of line extensions or replacement products (e.g. slightly altered versions of existing products).
- Demand for products that are bought less frequently by consumers tends to stabilize later than products that are bought more frequently by consumers.

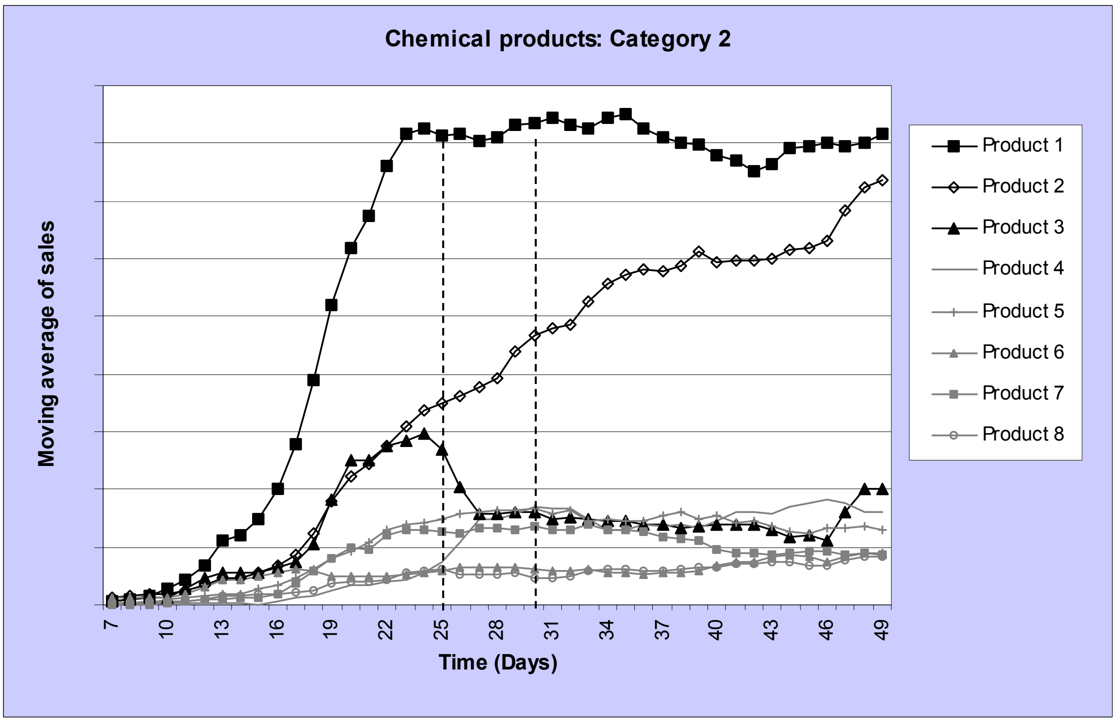

Figure 17. Sales profiles of product introductions in one of the examined product categories.

These observations are illustrated by Figure 17, which presents the eight largest products (measured in sales volume) introduced in one of ChemCo's categories. The products' sales are presented as seven-day moving averages in order to eliminate weekday-related variation. Product 1 is an extension of an existing product line and its demand stabilizes in less than 25 days after the introduction. Product 2 is a true novelty and its sales continue to grow even 50 days after the introduction. Product 3 experiences a demand peak at around 18 – 26 days after the introduction as the result of a promotion.

In addition to examining the products' sales profiles, scatter plots were used to investigate the relationship between the products' early sales and their stabilized sales volumes. Figure 18 presents a scatter plot of product introductions in CandyCo's main product category. The chart indicates a relationship between the products' average sales volumes in week 4 following their introductions and their average sales volumes several weeks later, in weeks 11 and 12 following their introductions. The result indicates that early sales data can, indeed, be used to predict the level at which demand for the new product will eventually settle.

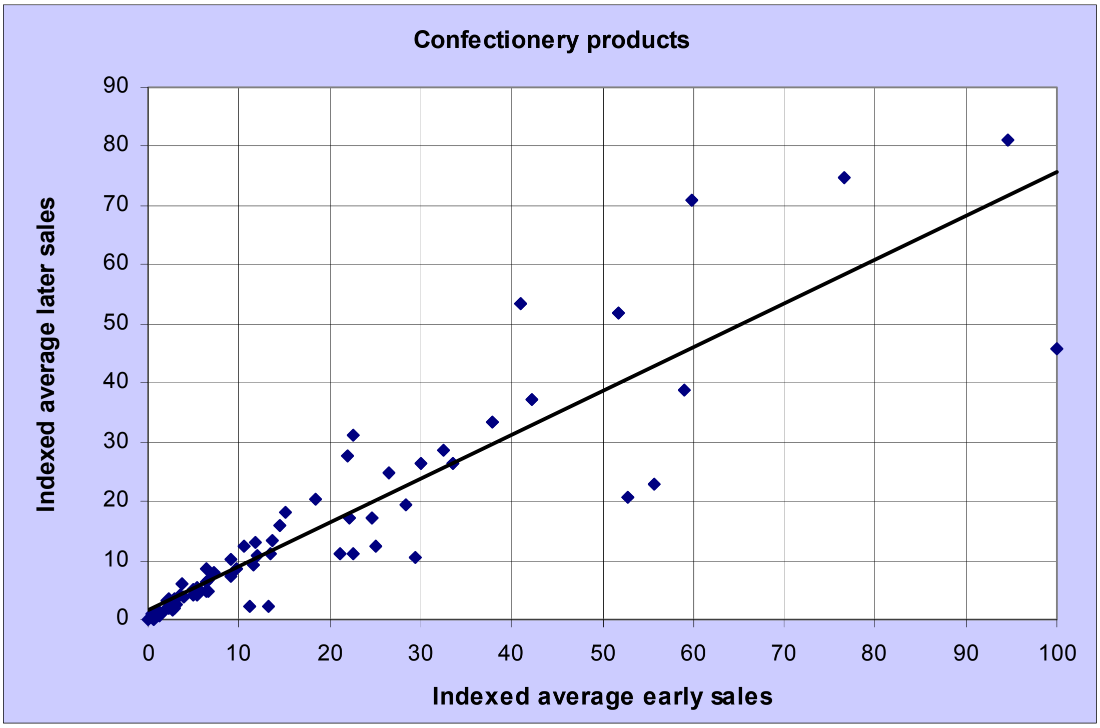

Figure 18. Relationship between early sales (average sales in week 4) and later sales (average sales in weeks 11 and 12) for 71 products in one of the examined product categories (R^2=0,814). (Each product is represented by a dot.)

Finally, correlations between the individual products' sales volumes at different points in time were calculated for products belonging to the two largest product categories examined (Table 19). The examination reveals rather strong correlations and, thus, corroborates the findings from the scatter plot analysis.

Table 19. Correlations between early and later sales for products belonging to two of the examined product categories.

	Chemical products* (Category 1)	Confectionery products**
Correlation between sales in week 2 and sales in weeks 11-12	0,97	0,81
Correlation between sales in week 4 and sales in weeks 11-12	0,98	0,90
Correlation between sales in week 6 and sales in weeks 11-12	0,99	0,91

*n = 23, **n = 71

4.3.4 Empirical results

The case companies found the results of the initial data analyses encouraging. Although the examined products had somewhat different demand patterns and different growth rates, the manufacturers' key account managers were, in general, able to detect the underlying logic explaining the products' behavior.

Since the data analyses only give a theoretical indication of the value of access to POS data in managing product introductions, the next step was to set up a pilot to test the usefulness of the data in practice.

Based on the results of the initial data analyses, the pilot implementation was set up as follows:

1. Two, four, six and eight weeks after the product introduction, RetailCo sends daily retail chain level POS data to the manufacturers for each of the new products.
2. Based on graphical representations of the products' sales profiles, the manufacturers' key account managers make adjustments to the products' forecasts, when necessary. A product's forecast is updated when its sales seem to have stabilized or when the product's sales are growing and have surpassed, or are just about to surpass, the current forecast. (Since both manufacturers' goods flow through RetailCo's logistics company's distribution center, forecasts are developed on the distribution center level, i.e. for the joint sales volumes of the logistics company's two owners.)
3. When necessary, the manufacturers' key account managers see to it that adjustments to the logistics company's inventory management parameters are suggested and discussed.
4. When the manufacturers' key account managers detect major differences between the initial sales forecast and an updated forecast, they inform RetailCo about this. RetailCo uses simulation to determine whether its store replenishment parameters need to be updated.

After the pilot, the companies decided to make information sharing a permanent part of their product introduction processes. The current information sharing process includes the four steps tested in the pilot.

Results attained by CandyCo

Already during the pilot phase, CandyCo managed to attain tangible benefits from its access to RetailCo's POS data. The key account manager estimates that access to POS data was a key factor in securing availability for at least two of the products included in the pilot. Without access to the POS data, there would have been a significant stock-out risk for these products, as their initial forecasts were much too low. Furthermore, the POS data enabled the company to correct overly optimistic forecasts at an early stage. CandyCo's key account manager comments:

> *"Using the data we [CandyCo] are able to react several weeks earlier than we could have by observing retailer order data alone."*

Owing to the flexibility of CandyCo's production process, forecast updates can very rapidly be taken into account in production. When a forecast is updated, it can, according to the key account manager, have an impact on production as early as within two weeks of the change. CandyCo also benefits from the forecast updates in controlling purchasing. However, the long lead-times of certain raw materials, especially packaging materials, sometimes reduce CandyCo's ability to react to an increase in demand. In some cases, even if CandyCo detects an acute need for additional raw material, it will have to wait several weeks or, in the worst case, months before receiving the replenishment. Of course, the data can, in some cases, still be used for making better decisions concerning order quantities.

The fact that the POS data available to the manufacturers only reflects RetailCo's sales whereas forecasts have to be developed for the logistics company's total demand, i.e. both for RetailCo's and the other owner's sales, is not considered a problem by CandyCo. The key account manager explains:

> *"Since we [CandyCo] know the penetration of our products in the different retailers' chains, we can draw fairly accurate conclusions even based on limited access to POS data."*

To summarize, CandyCo has been very pleased with the results of the pilot as well as the subsequently implemented permanent information sharing process. There are also some quantitative data available on the benefits that the company has attained through the information sharing effort. When comparing the period January 2002 – August 2002 before the pilot, with the period January 2003 – August 2003, i.e. the corresponding period following the implementation of the new information sharing process, CandyCo's forecast accuracy[*] for new products has increased by 7%. Furthermore, CandyCo's service level[†] (for all products, not just the recently introduced products) towards RetailCo's logistics company has increased by 2,6% when comparing these same two time periods.

CandyCo is currently developing a process for using the POS data available from RetailCo to update demand forecasts for its whole home market. So far, it has only used the data to update forecasts for the goods flowing through RetailCo's logistics company. In addition, CandyCo is looking for opportunities to insert the POS data into its forecasting system to be able to automatically produce graphs of the products' sales profiles and compare them with the most recent forecast information. Finally, CandyCo has initiated a development project with one of its packaging material suppliers in order to increase responsiveness upstream in its supply chain.

Results attained by ChemCo

In the case of ChemCo, the results of the information-sharing pilot were less convincing. Although the key account manager seemed to be able to make the right conclusions about the products' future demand, he was not as motivated to participate in the analyses as CandyCo's key account manager. This can be at least partly explained by ChemCo's forecasting process - forecasts are typically developed by demand planners communicating with the key account managers, rather than by the key account managers themselves, as in the case of CandyCo. ChemCo's key account manager also expressed some doubts concerning the value of putting down additional effort on forecasting:

> *"I'm a bit skeptical about this. Even if I put down additional effort [to analyze the POS data] there are no guarantees that my own customer will benefit… Even if my forecasting would secure additional goods, there is a risk of the goods going to one of our other customers… Also, production lead-times are so long that reacting a few weeks faster does not really make a difference".*

The key account manager's comment reflects the fact that ChemCo's production facilities are located abroad and serve the entire European market, which means that goods for the examined market are manufactured rather infrequently (typically in six or eight week cycles). In practice, although ChemCo's key account manager now gets access to information on the realized demand for a new product very rapidly, he thinks it is unlikely

[*] Forecast accuracy is here calculated as an average of the product's monthly forecast accuracies. The monthly forecast accuracies, in turn, are based on a comparison of the forecast developed one month ahead and realized sales.

[†] Service level is here calculated as an average of monthly service levels. The monthly service levels, in turn, measure the number of lines delivered vs. lines ordered.

that he will have an opportunity to impact on production until much later, reducing the benefits of POS data compared to customer sell-through or order data.

Despite the meager results of the pilot, sharing of POS data has been made part of the companies' processes for managing product introductions. Due to problems with ChemCo's enterprise resource planning system, the effect of the information sharing on the company's forecast accuracy or operational efficiency could not be quantified. However, the company's logistics manager finds it unlikely that the collaboration would have resulted in any improvements.

ChemCo is currently trying to develop a process for making use of the POS data, inspired by the good results attained by CandyCo. The company's aim is to find a way of feeding the POS data into their enterprise resource planning system and to have the system automatically generate forecast updates based on the data, minimizing the need for manual work. However, since POS data is available only from RetailCo, and forecasts need to be developed on the logistics company level, this is not straightforward. In addition, automating the interpretation of the POS data is considered challenging.

Results attained by RetailCo

The efficiency improvement attained by CandyCo has translated into benefits for the logistics company, and thus its owner, RetailCo. CandyCo's improved service level directly benefits the logistics company. Furthermore, more accurately set inventory parameters should lead to reduced inventories and fewer stock-outs in the future.

RetailCo's other goal was to attain increased store replenishment efficiency by using the forecast updates received from the manufacturers to set the parameters of its automatic store ordering system. However, as the store ordering system generates replenishments based on realized demand, it is not very sensitive to moderate forecast errors. Consequently, RetailCo has, so far, not needed to make any updates to its store replenishment parameters based on the forecast information received.

Nevertheless, encouraged by the results attained with CandyCo, RetailCo is planning to give more manufacturers access to POS data on product introductions. RetailCo's supply chain manager comments:

> *"We [RetailCo] are planning to give all of our major suppliers access to POS data on new products as part of a standard collaboration process that we are about to roll out."*

RetailCo has also started to share POS data on promotions with CandyCo and ChemCo. As the duration of the promotions is typically one month or less, promotional products have to be manufactured in advance, which means that there is little room for the manufacturers to react to realized demand. Yet, the companies find the examination of the products' promotional sales profiles and the resulting improved understanding of their behavior valuable.

Neither RetailCo nor the manufacturers have any interest in sharing or receiving POS data on standard products as long as the information exchange involves an element of manual work. Only products that have been recently introduced to the market, are affected by seasons, or are on promotion, are considered interesting from an information sharing point of view. CandyCo's key account manager comments:

> *"For regular products, order or sell-through data is accurate enough for operational decisions. Syndicated data, although somewhat delayed, provides the information that we [CandyCo] need for market analyses."*

4.3.5 Conclusions

Study 3 continues were Study 2 ended. It examines how, in practice, manufacturers can make use of access to POS data in managing recently introduced products.

In relation to Question 1 concerning the situations in which information sharing enables efficiency improvements in the supply chain, Study 3 provides two answers. Firstly, CandyCo's experiences demonstrate that access to POS data even from one important customer can be very valuable in managing product introductions. As suggested by Study 2, the company has been able to reduce the stock-out risk for new products, while at the same time being able to correct overly optimistic forecasts more rapidly than before. This has also benefited RetailCo through CandyCo's improved service levels towards the retailer's distribution center. Secondly, it was found that neither CandyCo nor ChemCo were interested in putting down effort on analyzing POS data for mature products with stable demand. As suggested by Study 2, the companies find that sell-through data from the companies' VMI implementation is sufficiently accurate for mature products.

In relation to Question 2 concerning the prerequisites for upstream members of the supply chain to be able to benefit from access to downstream sales data, Study 3 demonstrates that not all manufacturers are in the same position to benefit from information sharing. Based on the different experiences of CandyCo and ChemCo, it seems that a manufacturer's level of internal integration has an important impact on how downstream sales data can be interpreted and used for forecast updates.

In addition, the results of Study 3 indicate that the manufacturer's production planning and purchasing frequencies have a great impact on the usefulness of the data – if these frequencies are low, it may take a long time before it is possible to impact on production or purchasing, reducing the value of speeding up the information flow. Study 1 presented the production planning frequency as a key factor limiting the attainable benefits of using downstream sales data to level the production load. Study 3 shows that the production planning frequency also has an important impact on the attainable benefits of using downstream sales data to update forecasts for new products.

5 A STUDY ON COLLABORATIVE FORECASTING

5.1 Value of comparing retailer and manufacturer forecasts (Study 4)*

5.1.1 Purpose of the study

Study 4 provides answers to Question 3: What additional benefits and costs are associated with moving from sharing of downstream sales data to collaborative forecasting in supply chains?

More precisely, Study 4 examines the feasibility and value of implementing forecasting collaboration based on comparison of forecasts. The study looks at a retailer's and a manufacturer's forecasting processes and forecast accuracies in order to establish whether comparing forecasts could improve their forecasting performance. The study was inspired by the suggested benefits of combining retailer and suppliers forecasts (Aviv, 2001; 2002) and of the implementation of the CPFR process model (Fliedner, 2003; VICS, 1999).

5.1.2 Methodology

Study 4 uses a case study approach and examines the forecasting processes and forecast accuracies of a grocery retailer (TradeCo) and a consumer goods manufacturer (ChemCo).

Case selection

ChemCo is a large, multinational manufacturer of techno chemical products. It has specialized production plants located in several countries, serving global markets. The company sees improving its forecast accuracy as an opportunity to make its somewhat inflexible supply chain more efficient. It considers forecasting collaboration with its customers, the retailers, to be the best way of achieving reduced uncertainty and more reliable forecasts.

At the time of the study, ChemCo had been offered an opportunity to investigate the potential benefits of forecasting collaboration with one of its customers, TradeCo, a large grocery retailer operating in Northern Europe. This study describes the analyses conducted to examine the potential value of implementing CPFR-style forecasting collaboration based on comparison of the two companies' forecasts.

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*Results of this study have previously been presented in Småros, J. (2003), "Collaborative forecasting: A selection of practical approaches", International Journal of Logistics Research and Applications, Vol. 6, No. 4, pp. 245-258.

Data collection and analysis

Data on the forecasting processes of the two companies was collected through interviews and by reviewing documents. Interviews were conducted with one of TradeCo's category managers, its development director responsible for logistics, and one of its IT managers. From ChemCo's side, one of the company's key account managers as well as a person responsible for forecasting were interviewed. In addition, documents describing the processes for dealing with new product introductions, assortment changes and products to be discontinued were reviewed.

Data on forecasts was collected from the two companies' enterprise resource planning systems and compared to sales data received from TradeCo. The examination included 169 personal hygiene and household cleaning products and a time period of three months beginning with December 2001 and ending with February 2002. The comparison looked at differences in forecasts and forecast accuracies, when the differences seemed to be the largest and whether the differences appeared to be systematic. The findings were discussed and analyzed in co-operation with representatives of TradeCo and ChemCo.

5.1.3 Results

Differences in forecasting processes

When the companies first started discussing collaborative forecasting, they quickly realized that their planning and forecasting processes are rather different. TradeCo dealing with tens of thousands of products mainly relies on simple time-series forecasts, typically a moving average of historical sales, whereas ChemCo's much smaller product range makes it possible for it to use expert judgment to manually adjust statistical forecasts typically derived using exponential smoothing. In addition, the companies work with different planning horizons. As TradeCo's order-to-delivery lead-time is short – ranging from less than a day to a few days – the emphasis is on short-term forecasts needed for efficient purchasing and inventory management, i.e. for guiding daily purchasing decisions. ChemCo, on the other hand, needs to estimate demand several weeks or months ahead to cope with long production lead-times.

The difference in processes is clearly visible in the way that the companies deal with product introductions (Figure 19). To enable efficient production, ChemCo's sales company has to deliver a sales forecast to the production plant months before the product launch. This initial forecast is based on information on previous launches and on expert judgment. The forecast is updated when ChemCo's retail customers announce their assortment decisions and distribution plans for the product. After the product launch, ChemCo updates its forecast on a weekly basis using a combination of time-series methods, typically exponential smoothing, and qualitative estimates. TradeCo, on the other hand, does not need an exact forecast until it starts purchasing the new product. If the product is a new variant of an existing product, the previous product's sales history is used as the basis for forecasting. On the other hand, if the product is completely novel, TradeCo usually does not use any forecast at all, but instead purchases the product manually during the first months following the introduction. After some months, TradeCo starts using a moving-average forecast.

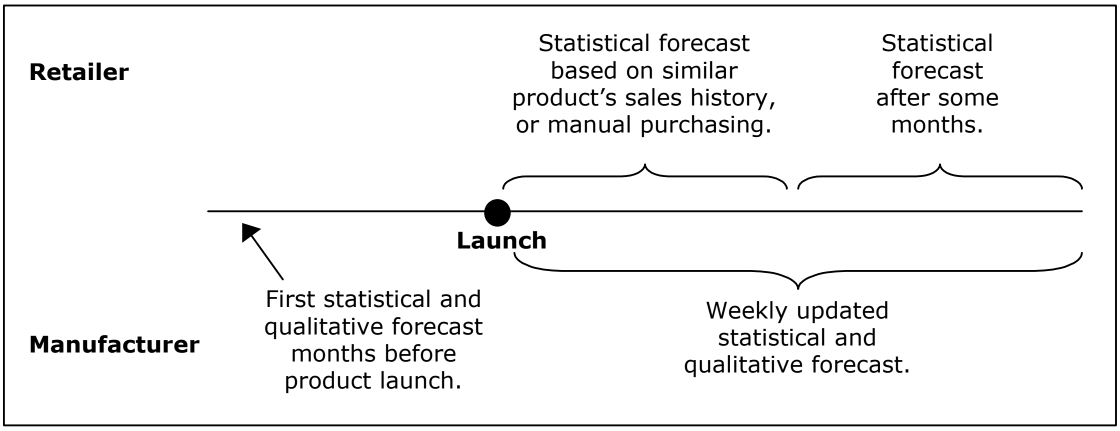

Figure 19. Retailer's and manufacturer's different forecasting processes for product introductions.

Differences in forecasts

The different processes also lead to different results. When comparing forecasts produced by ChemCo to those produced by TradeCo, significant differences were detected. In February 2002, forecast information extracted from ChemCo's and TradeCo's information systems was examined. The comparison seemed to reveal a pattern. TradeCo's forecast was much lower than ChemCo's mainly for recently introduced products ('Jan 02' products in Figure 20). TradeCo's forecast was also significantly lower for products introduced approximately 5 months earlier ('Aug 01' products in Figure 20). The forecast was to some extent lower for products introduced approximately 9 months earlier ('May 01' in Figure 20), although TradeCo's and ChemCo's forecasts for these products were, in general, similar. The products for which TradeCo's forecast was higher than ChemCo's were, on the other hand, mainly products that had been on the market for 9 months or more ('May 01' and 'Old' products in Figure 20).

It was anticipated that there would be some differences in the companies' forecasts. After all, TradeCo's moving-average forecast looks at history and was expected to react slower to changes than ChemCo's forward-looking, statistical and qualitative forecast. However, the magnitude of the differences was surprising, especially for the recently introduced products.

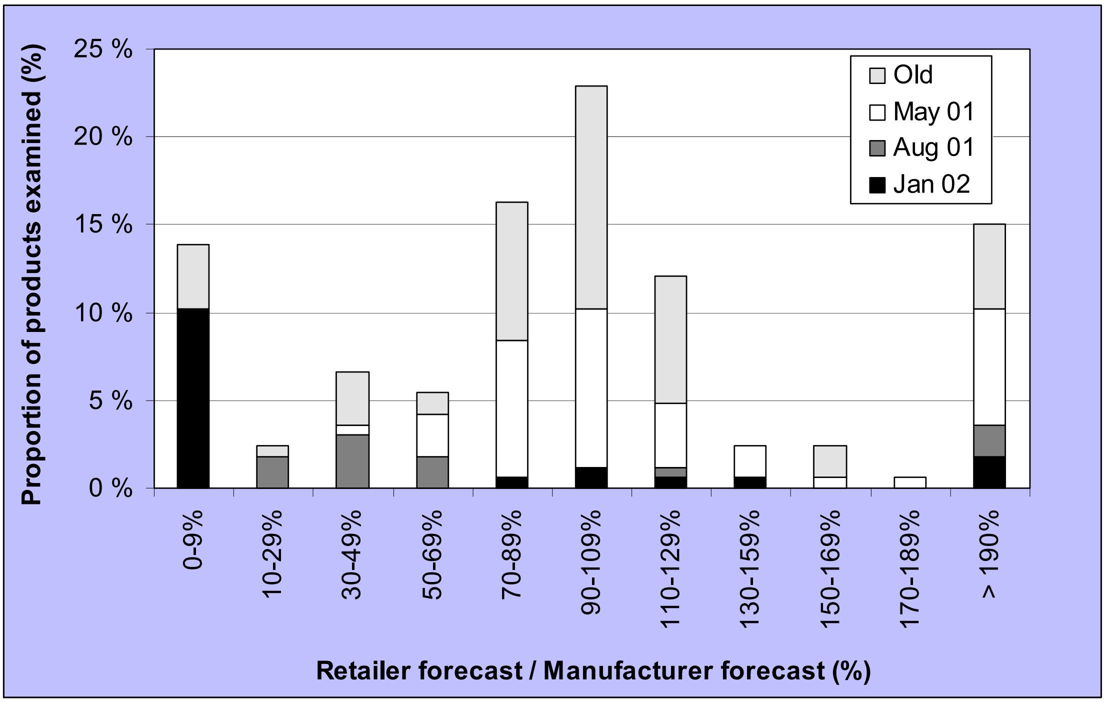

Figure 20. Retailer's forecast as a percentage of the manufacturer's forecast (a low percentage means that the retailer's forecast was notably lower than the manufacturer's, a high percentage that the retailer's forecast was notably higher than the manufacturer's).

Due to the detected differences in the companies' forecasts, it was decided to take a closer look at the products that had been introduced less than six months ago ('Jan 02' and 'Aug 01' in Figure 20) and examine how the forecasts corresponded to the actual outcome. When examining the forecast accuracies of TradeCo and ChemCo for these products (Figure 21), it became clear that there was room for improvement by both companies. However, ChemCo's forecast generally performed better than TradeCo's statistical forecast. Although ChemCo's forecast tended to be slightly inflated, the often significantly understated forecast of TradeCo was considered much more problematic. In fact, for some of the most recently introduced products, TradeCo did not use the forecast at all, but instead purchased the products manually (for these products the statistical forecast generated by the purchasing system is included in Figure 21 to enable comparison). It was also seen that ChemCo had more resources to invest in improving its forecasting accuracy.

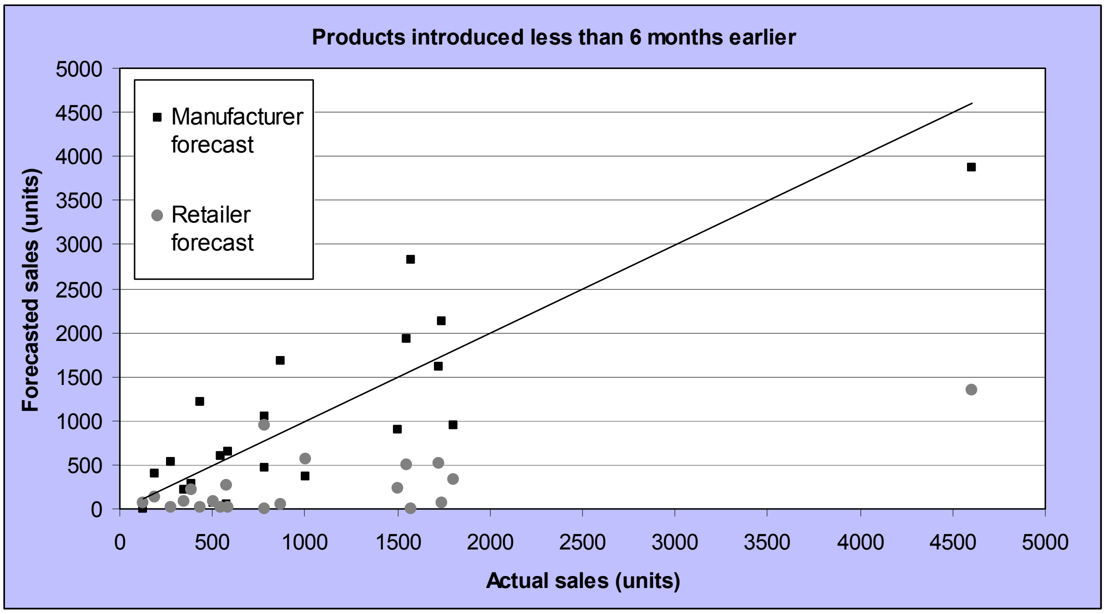

Figure 21. Retailer and manufacturer forecasts for new products plotted against actual sales (Each product is represented by a dot. Dots below the diagonal line indicate too low a forecast, dots above the line indicate too high a forecast.)

Based on the results of the analysis, it was suggested that the companies try out a new forecasting approach in which TradeCo would use ChemCo's forecast for product introductions. The companies agreed to set up a pilot project in which ChemCo would share its forecasts for its product introductions and TradeCo would use these forecasts as a basis for purchasing decisions until it had enough historical data to enable a switch to time-series forecasting.

Both companies are expecting to benefit from the collaboration. Two main benefits for TradeCo have been identified. Firstly, as ChemCo's forecast can be used to set inventory management parameters for new products, manual buying is no longer needed in the beginning of a product's life cycle. Secondly, if there is an improvement in forecast accuracy, TradeCo's service level to its stores is likely to increase. Improved store service is also the greatest benefit from ChemCo's point of view. ChemCo expects the reduced stock-out risk to translate into increased sales and aims to reinforce this effect by further developing its forecasting capabilities. Since the process is based on sharing of existing information, minimal additional work is required from either party.

5.1.4 Conclusions

In relation to Question 3 concerning the additional benefits and costs associated with collaborative forecasting as compared to information sharing, Study 4 presents an interesting result: An examination of the case companies' forecasts and forecast accuracies clearly shows that access to the retailer's forecasts would provide only limited, if any, value to the manufacturer. Especially for product introductions it would, in fact, be more beneficial to simply pass on the manufacturer's forecast to the retailer rather than to compare forecasts. This is due to the retailer's reliance on simple time-series forecasting and manual purchasing, whereas the manufacturer is using a combination of quantitative and qualitative forecasting approaches in managing its product introductions.

These findings are in striking contrast with the assumptions of, for example, Raghunathan (1999) and Aviv (2001; 2002), who build their analytical models on the premise that retailers can produce accurate and reliable forecasts (Raghunathan, 1999) and that combining retailer and manufacturer forecast information always improves the quality of the forecast (Aviv 2001; 2002). If these assumptions are invalid, as suggested by the results of the study presented here, the results of these studies are also rendered invalid.

Furthermore, the case retailer considers the investment needed to improve its forecasting performance too high in relation to the attainable benefits. This suggests that retailers may have less need for improving forecast accuracy than manufacturers. Drawing such a conclusion based on one observation is, of course, rather speculative. However, if this is found to be a more generally valid observation, it presents a new and interesting angle to the discussion concerning collaborative forecasting. In none of the long lists of potential obstacles to successful implementation of collaborative forecasting (see, for example, Barratt, 2004; Fliedner 2003; Skjoett-Larsen et. al, 2003; McCarthy and Golicic, 2002) has the different forecasting needs of companies located at different echelons of the supply chain been mentioned.

6 STUDIES CONTRASTING INFORMATION SHARING AND COLLABORATIVE FORECASTING

6.1 Comparison of collaborative forecasting and sharing of sales data (Study 5)

6.1.1 Purpose of the study

Study 5 provides answers to Question 3: What additional benefits and costs are associated with moving from sharing of downstream sales data to collaborative forecasting in supply chains?

More precisely, Study 5 contrasts two different kinds of collaborative forecasting with sharing of downstream sales data in order to examine the feasibility and value of the different approaches.

The inspiration for this study came from what seems to be a contradiction between research and practice. Although many academics argue that tightened supply chain integration in the form of collaborative forecasting should provide greater benefits than sharing of sales data (see, for example, Barratt and Oliveira, 2001; Lee et al. 1997; Zhao et al., 2002), companies have been slow to adopt forecasting collaboration (Barratt, 2004; Corsten, 2003; Sliwa, 2002). Although some attempts have been made to explain why implementation has been so difficult, the results to date have been long lists of potential problems, including many of the "usual suspects", such as lack of trust or lack of shared targets. This makes it hard to distinguish whether forecasting collaboration has stumbled on the traditional difficulties related to the implementation of new practices, or whether there are some inherent problems with the concept of collaborative forecasting.

6.1.2 Methodology

Study 5 employs a case study approach. In order to allow for cross-case analysis and comparison of collaborative forecasting and sharing of downstream sales data, the two cases presented in Study 3 have here been complemented with two additional cases focusing on forecasting collaboration. A total of four retailer–manufacturer development efforts are, thus, examined.

Case selection

The examined retail company, RetailCo, operates in Northern Europe and is considered progressive in the area of logistics. In the late 1990's, RetailCo got interested in CPFR among the first in its market and has since then been involved in several collaboration projects. RetailCo presents an interesting research subject for two reasons. Firstly, since the company is skilled in logistics, the success or failure of the development projects examined is unlikely to be caused by the retailer lacking capabilities that other retailers have, making it possible to focus on other explaining factors. Secondly, the fact that the company is and has been involved in several collaboration projects makes it possible to compare projects to look for similarities and differences in their scopes and focus, information technology requirements, the collaboration practices employed, the difficulties and opportunities faced, and how these factors have affected the outcomes of the projects.

The examined manufacturers were selected based on their involvement in development projects with the retailer. Although the manufacturer sample could not be freely composed, the differences between the manufacturers and their collaboration efforts with RetailCo enable interesting comparisons. Two of the companies are producers of fresh goods with production facilities in the examined region. The other two are manufacturers of dry goods - one a large multinational company with production plants in several different countries, the other also an international, but smaller manufacturer with its main production facilities in the examined region. There are also differences in focus between the development projects. One of the projects set out to implement the VICS CPFR process model, but the other three were more limited in scope and targeted either promotions or new product introductions. The development projects and the manufacturers are presented in Table 20 (Cases 3 and 4 are the same as in Study 3.)

Table 20. Cases examined in Study 5.

	Focus of development project	Manufacturer involved in project
Case 1	CPFR-style collaboration	DairyCo, a national producer of dairy products
Case 2	Planning and forecasting of promotions	MeatCo, a national producer of meat products
Case 3	Updating forecasts for new products	CandyCo, an international producer of confectionery products
Case 4	Updating forecasts for new products	ChemCo, a multinational producer of techno chemical products

Data collection and analysis

The development projects were monitored during a period of a little more than a year, starting in July 2002 and ending in September 2003. In the beginning of the observation period, two of the development projects had already been running for some time and two were just about to start. In the end of the observation period, the development projects were either ended, being ended, or in an evaluation phase.

At the start of the research some *a priori* constructs were defined, but as the research progressed the constructs were refined and new ones added. Since the data collection effort included frequent contact with many persons involved in the development projects, information on several topics was collected. However, the most interesting angles of investigation turned out to be: the characteristics of the piloted collaboration practices (i.e. the contents and scope of the collaboration processes employed in the development projects), the benefits and costs of the piloted collaboration practices (both realized and expected), the relevance of the piloted collaboration practices to the companies involved (compared with other opportunities to work together), and the scale-up prospects of the piloted collaboration approaches. The constructs and their operationalization are presented in Table 21.

Table 21. Research constructs and data collection protocol used in Study 5.

Research constructs	Data collection protocol
Characteristics of piloted collaboration practices ▪ Scope of the piloted collaboration ▪ Information sharing ▪ Collaborative activities	Information on the collaboration process and scope was collected through direct observation as well as through semi-structured interviews and company reports.
Benefits and costs of the piloted collaboration practices ▪ Immediate tangible and intangible benefits ▪ Expected future benefits of the collaboration if continued ▪ Costs and investments during the pilot phase ▪ Expected costs and investments related to a potential scale-up of the collaboration	Benefits, costs, and investments were evaluated through semi-structured interviews. Quantitative measurement of benefits was conducted using forecast accuracy and service level data when applicable.
Relevance of the piloted collaboration practices ▪ Relative importance of the piloted collaboration practices compared to other opportunities for manufacturer and retailer to work together	The relative importance of the piloted collaboration approaches was evaluated by the case companies during a workshop.
Scale-up prospects of piloted collaboration practices ▪ Company plans to turn piloted collaboration practice into permanent process ▪ Company plans to scale-up piloted approach to include new partners	The companies' scale-up plans and attitudes were examined through semi-structured interviews and direct observation of project meetings.

To enable triangulation, data on each of the development projects were collected from several information sources (Voss et al., 2002). In all cases, the author had access to documents establishing the project's goals, planned contents, and schedule. In addition, semi-structured interviews with manufacturer representatives were conducted (see Appendix III for the questionnaire). Throughout the study, informal discussions with the retailer's CPFR manager and one of its logistics planners took place. In three of the cases, the author also regularly attended project meetings. In the one case where the author did not attend project meetings (Case 1), additional interviews were conducted as well as internal company reports used. Different types of data analyses and presentations available were also used in the research. Table 22 summarizes the information sources used in each of the cases studied.

Table 22. Information sources used in Study 5.

	Documentation	Interviews	Direct observation
Case 1	▪ Project plan ▪ Report summarizing results from first test phase ▪ Report summarizing results from second test phase ▪ Project presentations	▪ Semi-structured interview with DairyCo's key account manager ▪ Interview with one of DairyCo's demand planners (developer of demand forecasting tool used in project) ▪ Semi-structured interview with RetailCo's CPFR manager ▪ Interview with one of RetailCo's logistics planners (developing forecasts in the project) ▪ Informal discussions with representatives of RetailCo	-
Case 2	▪ Project plan ▪ Forecast accuracy analyses	▪ Semi-structured interview with MeatCo's category manager ▪ Informal discussions with representatives of RetailCo	▪ Regular participation in project meetings
Case 3	▪ Project plan ▪ Demand and forecast accuracy analyses ▪ Quantitative performance data ▪ Project presentations	▪ Semi-structured interview with CandyCo's key account manager ▪ Informal discussions with representatives of RetailCo	▪ Regular participation in project meetings ▪ Participation in CandyCo's internal forecasting meetings
Case 4	▪ Project plan ▪ Demand analyses ▪ Qualitative performance assessments	▪ Semi-structured interview with two of ChemCo's key account managers ▪ Informal discussions with representatives of RetailCo	▪ Regular participation in project meetings ▪ Participation in ChemCo's internal forecasting meetings

In addition, in spring 2003, a workshop involving RetailCo and the four manufacturers took place. The aim of the workshop was to analyze and compare collaboration experiences and to prioritize between the different collaboration approaches available. The total number of participants was twenty. Thirteen participants were from the retailer side, representing both persons directly involved in the development projects, mainly category managers and logistics planners, and management. Seven participants, mainly key account managers, were present from the manufacturer side.

Following Eisenhardt's (1989) recommendation, the data analysis consisted of two different phases: within-case analysis and cross-case pattern search. First, data from different sources were brought together to form a coherent picture of each of the cases as a separate entity. This phase of the research resulted in case descriptions that were checked by key informants in order to ensure validity (Stuart et al., 2002). Next, cases were compared in order to identify potential cross-case patterns.

6.1.3 Cases

Case 1: Modified CPFR

Case 1 is a development project that involved the retailer, RetailCo, and DairyCo, a manufacturer of dairy products. The project set out to increase forecast accuracy and improve replenishment efficiency at the store level. Focusing on the store level rather than, for example, on the distribution center level was a natural choice since DairyCo employs direct store delivery. This also made it possible to look at the whole supply chain, down to the end customers, which was considered important both by RetailCo and DairyCo.

Table 23. Collaboration process employed in Case 1.

Phase	Step	Timeframe
Preparation	▪ Collaboration agreement	Start of collaboration
Planning	▪ Joint assortment decisions ▪ Joint identification of changes, promotions, seasons etc.	4 months – 1 month
Forecasting	▪ Joint creation of chain level sales plan (using POS data) ▪ Joint examination of sales plan and exceptions ▪ Joint creation of store level sales plan (using POS data)	1 months – 2 weeks
Replenishment	▪ Creation of joint store replenishment plan ▪ Replenishment based on plan and realized demand	1 week – 1 day

The starting point of the development project was the VICS CPFR process model. The process model was, however, soon slightly adapted (see Table 23). A key collaboration step of the new process model was the joint identification of upcoming demand changes, such as promotions and seasons. This information together with RetailCo's POS data was then used to create chain level sales plans. The chain level sales plans were, using POS data, translated into replenishment plans for the individual stores. The replenishment plans together with data on realized demand were used for controlling store replenishments.

When comparing the new collaboration process that was piloted in the development project to the two companies' traditional way of doing business together, two main differences can be identified. Firstly, the piloted process introduced more structure to the discussions concerning upcoming demand changes, such as promotions and seasons, as well as more formal documentation of the results of the discussions in the form of a sales plan. Although the traditional business process also includes discussions concerning future events, the purpose of these discussions is to notify DairyCo of RetailCo's plans rather than to jointly plan and evaluate the impact of the changes. Secondly, and more importantly, the new collaboration process included active demand forecasting by RetailCo's central organization. Normally, no centralized forecasting takes place and the responsibility for managing the product flow to the stores, and thus for forecasting, resides with the store personnel placing replenishment orders. During the pilot, RetailCo's category manager discussed events and forecasts at regular sales planning meetings with DairyCo. In addition, one of RetailCo's logistics planners in co-operation with a demand planner from DairyCo's demand management organization developed detailed store-specific demand forecasts.

The development project included two test phases in which the new collaboration process was tested for a little less than twenty products. In the first phase, replenishment of a dozen stores representing different store formats was conducted in accordance with the new collaboration process. In the second phase, the impact on store replenishments was evaluated using calculations based on POS data rather than by actually replenishing stores based on the replenishment plans developed. In the test phases, different forecasting approaches including several time-series models and expert judgment were evaluated. The two test phases were carried out without the use of advanced IT tools. Forecasting was done using spreadsheet models and information sharing was enabled by an electronic workspace rented from a telecom company. IT did not pose a significant problem or investment to the development project. However, both DairyCo's key account manager and RetailCo's CPFR manager agree that a large-scale rollout of the piloted collaboration approach would require extensive system support.

When looking at the results of the development project, it can be concluded that the concrete goal of increased store level forecast accuracy was not achieved. Although the attained chain level forecast accuracy was acceptable, the store level forecast accuracy attained in the tests did not meet the targets set in the project plan. Neither the time-series models tested nor expert judgment provided the desired results. One of RetailCo's logistics planners comments as follows:

> *"Producing accurate store level forecasts turned out to be rather difficult… During the project it became clear that we [DairyCo and RetailCo] did not have enough knowledge about forecasting methods. It was also very difficult to extract data needed for forecasting, such as information on promotions, from our [RetailCo's] IT systems."*

There were other difficulties as well. Since RetailCo does not normally employ a centralized forecasting process, producing forecasts for use in the two tests proved laborious. To be able to do the same thing on a larger scale, RetailCo would need to invest in developing its demand management processes, or as the RetailCo's CPFR manager puts it:

> *"Scaling up this kind of detailed forecasting collaboration would require us [RetailCo] to establish a demand planning department corresponding to that of the supplier's. From our point of view that would be an immense investment."*

Despite the problems, both companies agree that the development project did achieve some positive results. The companies now better understand which products are difficult to manage and for which collaboration is not worth the effort; the main finding of the first test phase was that there is no need to spend time on forecasting demand for products that are neither on promotion nor affected by seasonality. In addition, several forecasting approaches have now been tested and discarded, which means that the companies have a better picture of what the forecasting challenges and requirements are.

The piloted collaboration process has not been turned into a permanent process, mainly due to RetailCo's reluctance to invest in increased demand planning resources. However, a streamlined version of the process, focusing on the planning part of the process, has been taken into use for part of DairyCo's products. This has resulted in more systematic sharing of information on upcoming demand changes, such as promotions and seasons, which is considered a step in the right direction from DairyCo's point of view. Since the streamlined process requires only little additional work from RetailCo, the company does not perceive participating in this kind of collaboration too costly, although the expected benefits to the company are limited.

Case 2: Planning and forecasting of promotions

As mentioned above, RetailCo does not employ a formal demand forecasting process. Although some of the retailer's category managers do some forecasting of promotional demand and discuss the forecasts with manufacturers, there are significant individual differences between the category managers. Moreover, forecasting is not supported by RetailCo's IT systems and forecasts are neither registered nor monitored. The objective of the second development project examined was to increase forecast accuracy for promotions by implementing a collaborative forecasting process and creating a new forecasting tool. An additional goal was to introduce more efficient monitoring of the financial impact of promotions. The development project involved RetailCo and a national producer of meat products, MeatCo.

The first task of the development project was to add collaborative forecasting of promotions to the companies' current category management process. In the new process, a demand forecast is developed based on historical data on previous promotions four weeks prior to the beginning of a promotion and then collaboratively adjusted by RetailCo's category manager and MeatCo's key account manager. The second task was to create a tool for viewing historical promotion data – both on MeatCo's and its competitors' promotions – to support forecasting and decision-making. The developed tool is very simple; it is essentially a database containing historical promotion data, such as sales before, during, and after a promotion, promotion type, and substitute products affected by the promotion. The tool also includes financial data. Originally, the goal was to use the forecasting tool to automatically produce statistical forecasts, but due to the limited amount of historical data available, changing promotion types, and the large number of different promotions, a more qualitative approach in which the data is used for supporting judgmental decisions was adopted.

Collaborative forecasting as implemented in the development project did not notably increase forecast accuracy. In addition, although the forecasting tool developed is appreciated by its users, its impact on forecast accuracy has, so far, not been significant. MeatCo's key account manager had already before the start of development project managed to do a reasonably good job of forecasting promotions based on his knowledge, experience, and MeatCo's historical sales data.

Although the main goal of the project was not achieved, the project delivered some important intangible results from RetailCo's point of view. Firstly, it demonstrated how little forecasting actually takes place in its category management organization. Secondly, the project showed how difficult it currently is to access historical data on promotions; the data needs to be manually collected from several systems. RetailCo now understands the human and IT resources it needs to develop if it aims to starts producing demand forecasts in the future. According to the CPFR manager:

> *"This is especially important since we [RetailCo] are planning to start managing promotions in a more centralized way, which requires centrally developed forecasts. Being able to extract the right historical data in the right format from our systems is important both for our internal processes and for collaboration with suppliers."*

Although the forecasting process and tool did not significantly increase forecast accuracy, it makes it possible for people with little experience to develop fairly accurate forecasts. This has decreased MeatCo's dependence on its key account manager, who is soon to retire. MeatCo is also expecting more benefits to come in the future. When more data on promotions are collected, forecast accuracy is likely to improve. In addition, MeatCo is hoping that access to better information on past promotions will enable the two companies to develop more effective promotions in the future by focusing on the right types of promotions and the right products. MeatCo's category manager explains:

> *"If we [MeatCo] can encourage our customer [RetailCo] to make financially better promotion decisions, both of our companies can get better returns on our investments in promotional activities."*

The development project has now been terminated and the piloted approach has been turned into a permanent process. RetailCo is currently looking for a technical solution to automate data collection and make the process more efficient. In the future, it is planning to engage in similar collaboration with other manufacturers.

Case 3: Updating forecasts for new products

The third development project involved RetailCo and an international confectionery manufacturer, CandyCo. The development project focused on new product introductions. RetailCo agreed to give CandyCo access to POS data on new products to enable the manufacturer to update its sales forecasts as rapidly as possible. (The development project is presented in more detail in Study 3.)

After promising data analyses, a pilot was set up to test the approach in practice. For a set of new products, RetailCo e-mailed the manufacturer POS data on the products' sales two, four, six and eight weeks after their introduction to market. Graphs illustrating the development of the products' sales over time were produced using spreadsheet software. Based on the graphs, CandyCo's key account manager updated forecasts for the products. Access to POS data made it possible for CandyCo to quickly identify stock-out risks as well as to reduce overly optimistic forecasts.

After the successful pilot, RetailCo agreed to deliver POS data on new products to CandyCo on a permanent basis. The companies also agreed to deepen their collaboration and link it more tightly to RetailCo's store replenishment system. The current process is as follows: CandyCo provides the retailer with a first demand forecast for new products. The forecast is used for determining product shelf space and store replenishment parameters. Then, after receiving POS data, CandyCo analyses the data, adjusts its own forecast, communicates the changes to RetailCo's distribution center, and communicates major changes to RetailCo's logistics and category management personnel, who can use the information to update store replenishment parameters. So far, RetailCo, has not, however, needed to update its store replenishment parameters, which for dry consumer packaged goods are not very sensitive to moderate forecast errors.

When looking at the results of the development project, it can be concluded that the goal of increasing forecast accuracy for new products was met. Access to undistorted sales data straight from the retail chains has enabled CandyCo to rapidly update its forecasts and increase their accuracy. A 7% increase in forecast accuracy for new products was detected when comparing corresponding periods before and after the start of the collaboration. Since CandyCo has invested in increasing the responsiveness of its production process, it has also been able to update its production schedules based on the forecast updates. This is reflected in lowered inventories as well as in the manufacturer's average service level (not just for new products) towards RetailCo's distribution center. The service level has increased with 2,6% when comparing corresponding periods before and after the start of the collaboration. However, long-lead times and large economic order quantities for, for example, packaging materials has in some cases limited CandyCo's ability to benefit from the forecast updates.

Currently, the companies are fine-tuning and streamlining their co-operation. They are looking for an IT solution to support the information exchange. In addition, they are exploring potential other uses of manufacturer access to POS data. RetailCo is planning to offer POS data on new product introductions to other manufacturers as well.

Case 4: Updating forecasts for new products

The last one of the development projects examined involved RetailCo and a large multinational manufacturer of techno chemical products, ChemCo. The project followed an almost identical pattern as in Case 3. In fact, the two development projects were conducted in parallel. (The development project is presented in more detail in Study 3.)

However, in this case the results of the pilot were less convincing. Although ChemCo's key account manager seemed to be able to make the right conclusions about the products' future demand, he was not as motivated to participate in the analyses as CandyCo's key account manager. This can be at least partly explained by ChemCo's forecasting process - forecasts are typically developed by demand planners communicating with the key account managers, rather than by the key account managers themselves. The key account manager also expressed some doubts concerning the value of putting down additional effort on forecasting. Long production intervals and limited production flexibility make the links between local demand planning and global production planning weaker than in Case 3.

Due to problems with ChemCo's enterprise resource planning system, the effect of the development project on the manufacturer's forecast accuracy could not be quantified. However, ChemCo's representatives found it unlikely that the collaboration would have resulted in any improvement.

Despite the somewhat thin results, the pilot has been turned into a permanent process. ChemCo is, however, still working on developing its forecasting processes to enable more effective use of the data, inspired by the example of CandyCo.

Workshop

In spring 2003, a workshop for the companies involved in the four development projects was arranged. The aim of the workshop was to analyze and compare collaboration experiences. The main content of the workshop was a group work. The group work focused on the companies' needs for information sharing and collaboration in the context of product introductions, other assortment changes, promotions, and seasons. Retailer representatives and manufacturer representatives formed their own groups and were advised to identify collaboration needs strictly from their own point of view, without taking into consideration their counterparts' needs at all at this stage. Afterwards, the results were discussed in mixed groups including both retailer and manufacturer representatives.

Table 24. Retailer's main information sharing and collaboration needs.

Product introductions	Assortment changes
▪ Receiving initial demand estimates from manufacturers ▪ Receiving availability and risk information from manufacturers ▪ Receiving analyses on product's target chain and potential substitutes or replaceable products from manufacturers	▪ Further development of current category management co-operation ▪ Mutual sharing of consumer information collected through, for example, market research ▪ Receiving timely information on product changes from manufacturers
Promotions	**Seasons**
▪ Receiving demand estimates and availability guarantees from manufacturers ▪ Manufacturer participation in monitoring and development of promotional activities ▪ Joint classification and definition of promotions	▪ New way of operating: replacing stores' advance orders with a chain level forecast and replenishing stores based on realized demand ▪ Receiving information on previous seasons from manufacturers ▪ Co-operation in scheduling of deliveries, receiving information on different transport options (e.g. additional delivery days) from manufacturers

RetailCo's representatives emphasized the need for receiving rough level demand estimates for product introductions, promotions, and seasons from the manufacturers. Due to the introduction of a centrally managed store replenishment system, RetailCo's category managers will in the future need to produce demand forecasts for these situations. Since most of the category managers have little or no experience of forecasting, they are looking for support from the manufacturers. Other identified collaboration needs were, for example, manufacturer participation in monitoring of promotions and developing and classifying promotional activities. The most important information-sharing and collaboration needs from RetailCo's point of view are presented in Table 24.

Interestingly, when comparing the results of the retailer and the manufacturer groups, there are some notable differences. The manufacturer groups emphasized faster decision-making. If RetailCo could make binding decisions concerning new products, assortment changes, promotions, and seasonal products earlier, it would give the manufacturers more time to react. One manufacturer representative commented:

> *"Currently, many of us [the manufacturers] need to start production of a promotional product before the retailer has even committed to running the promotion."*

The manufacturers also wanted access to POS data on product introductions and promotions. The most important information sharing and collaboration needs from the manufacturers' point of view are presented in Table 25.

Table 25. Manufacturers' main information sharing and collaboration needs.

Product introductions	Assortment changes
▪ Receiving a binding decision concerning new products and their distribution as early as possible from the retailer ▪ Access to retailer's POS data on recently introduced products ▪ Access to retailer's information on different chains' customer profiles	▪ Receiving a binding decision concerning products and their distribution as early as possible from the retailer ▪ Joint planning so that the target store coverage can be attained as soon as possible ▪ Receiving information on store assortment profiles and their corresponding sales volumes from retailer
Promotions	**Seasons**
▪ Receiving a binding decision concerning promotions as early as possible from the retailer ▪ Access to retailer POS data before, during, and after promotions ▪ Receiving long-term promotion plans from the retailer	▪ Receiving a binding decision concerning seasonal products and volumes as early as possible from the retailer ▪ Joint planning of demand volume and distribution ▪ New way of operating: receiving chain level demand forecasts and replenishing stores based on realized demand.

6.1.4 Cross-case patterns

After looking at each of the development projects separately, the cases were compared in order to identify potential patterns. The comparisons are presented in Tables 26 - 29 and briefly explained in the text.

When examining the companies' plans to scale-up the piloted collaboration practices, it can be noticed that the companies have, in most cases, decided to move on from pilot project to implementing a permanent process and that they are also in many cases interested in extending the collaboration to include other companies (Table 26).

Table 26. Scale-up prospects of the piloted collaboration practices.

	Case 1	Case 2	Case 3	Case 4
Plans to turn pilot into permanent process	A decision to continue with a streamlined version of the piloted collaboration practice has been made. The limited implementation (only part of the process and only some of the products) is caused by RetailCo's reluctance to continue with the piloted collaboration process.	The piloted collaboration process continues on a permanent basis, although it is still operated manually. Both RetailCo and MeatCo are willing to invest in automation of the process.	The piloted collaboration process continues on a permanent basis, although it is still operated manually. Both RetailCo and CandyCo are willing to invest in automation of the process.	The piloted collaboration continues on a permanent basis, although it is still operated manually. RetailCo is willing to invest in automation of the process, but ChemCo has not discussed any concrete actions.
Plans to scale-up pilot to include new partners	DairyCo would like to involve all major customers in this kind of collaboration. RetailCo, however, is not interested in scaling-up even the streamlined version of the collaboration process to include new partners.	RetailCo is planning to offer similar collaboration to other manufacturers. MeatCo is interested in engaging in similar collaboration with other retailers.	RetailCo is planning to offer similar collaboration to other manufacturers. CandyCo is interested in engaging in similar collaboration with other retailers.	RetailCo is planning to offer similar collaboration to other manufacturers. ChemCo has less interest in the collaboration.

RetailCo is planning to scale up all of the piloted approaches, except for one. The collaboration process tested in Case 1 is considered too laborious compared to the potential benefits it can bring. Why is Case 1 different from the other cases? The answer can be found by examining the collaboration practices employed in the development projects (Table 27). Case 3 and Case 4 focused on sharing of POS data and required little resources from RetailCo. Both Case 1 and Case 2 included collaborative forecasting, but the scope of the collaboration in Case 2 was significantly narrower (forecasting of only promotional products), forecasting took place more seldom (monthly rather than weekly) and on a higher level (chain rather than store level), and the manufacturer took more responsibility for forecasting (discussions based on manufacturer's suggestions) in Case 2 than in Case 1. These differences made the approach tested in Case 2 feasible and the approach tested in Case 1 unfeasible from RetailCo's point of view. This is also reflected in the investment needed to scale-up the collaboration practices (Table 28): The collaboration practice piloted in Case 1 would have required RetailCo to invest in developing a demand management department, a much larger commitment than the IT investments needed to scale-up the other piloted practices, and something that RetailCo was not willing to do.

Table 27. Characteristics of the piloted collaboration practices.

	Case 1	Case 2	Case 3	Case 4
Scope of collaboration	Both chain and store level planning and forecasting for different types of products.	Planning and forecasting of promotions on a chain level.	Chain level forecasts for new products.	Chain level forecasts for new products.
Information sharing and collaborative activities	Both information sharing (POS data shared by RetailCo) and collaborative forecasting on a weekly basis.	Both information sharing (POS and other promotional data shared by RetailCo) and collaborative forecasting of promotions on a monthly basis.	Information sharing (POS data shared by RetailCo, forecast shared by CandyCo) for new products.	Information sharing (POS data shared by RetailCo, forecast shared by ChemCo) for new products.

When examining the manufacturers' interest in scaling up the collaboration approaches, it can be observed that in all cases, except for Case 4, the manufacturers are very positive about a potential scale-up. This is an interesting observation for two reasons. Firstly, it is noteworthy that DairyCo, the manufacturer in Case 1, did not experience the same resource problems as RetailCo in participating in CPFR-style collaboration even on a very detailed level. Contrary to the retailer, DairyCo has a dedicated forecasting organization. Secondly, it is interesting to compare the attitudes of the manufacturers involved in Case 3 and Case 4. CandyCo, the manufacturer in Case 3, is enthusiastic about the collaboration, whereas ChemCo, the manufacturer in Case 4, despite the identical content of the two development projects, has very limited interest in scaling up. By looking at the results attained by the two manufacturers, it becomes clear that although CandyCo has managed to benefit significantly from its access to retailer POS data on new products, ChemCo has not attained any benefits (Table 29). Due to problems with infrequent production runs as well as lack of internal integration between sales and demand planning and between the local sales organization and global production, ChemCo has experienced significant difficulties in benefiting from and motivating its personnel to use the POS data made available by RetailCo.

When examining the costs related to the piloted collaboration practices, and especially the costs related to a scale-up of the pilots, it can be observed that most of the practices require little additional work if the scale-up is supported by IT. The exception is Case 1 – causing RetailCo's reluctance to scale-up, as discussed earlier. All approaches, however, do need some level of investment in IT to enable efficient information sharing (e.g. manufacturer access to retailer POS data) and, potentially, to support inter-company collaboration (e.g. electronic workspaces for joint review and editing of data), although not necessarily any specific CPFR tools. These investments concern both RetailCo and the manufacturers. In addition, RetailCo needs to invest in its own capability to collect and report data, especially promotional data, not only to enable collaboration but also to support the planned implementation of centralized control of store replenishments. All companies agree that these investments in IT are necessary and that they need to be made before large-scale collaboration can take place. In fact, RetailCo has already started to develop its internal IT systems and both the retailer and the manufacturers have expressed their willingness to participate in developing information-sharing and collaboration solutions.

Finally, a fruitful angle of investigation is examining the relative importance of the piloted collaboration practices compared to other potential collaboration forms from the retailer's and the manufacturers' viewpoints (Table 29). An interesting observation is that there are differences in the manufacturers' and the retailer's perception of relevance in all cases. Typically, the collaboration aspects that are considered highly relevant by RetailCo, i.e. receiving manufacturer input (rough demand estimates) and support (e.g. by identifying seasonal changes) when forecasting changing demand, are considered only moderately relevant by the manufacturers. The manufacturers do consider forecasting to be important, but they are already comparatively good at it. The manufacturers' main interests are getting access to more accurate sales data and receiving binding decisions on upcoming activities earlier. These are, however, either considered only moderately relevant from RetailCo's point of view (sharing of POS data) or not very relevant at all, and just barely touched on in the development projects (earlier decision-making).

Table 28. Benefits and costs of the piloted collaboration practices.

	Case 1	Case 2	Case 3	Case 4
Realized benefits	▪ No immediate tangible benefits to RetailCo or DairyCo ▪ Improved process for and retailer commitment to information sharing regarding e.g. promotions benefits DairyCo	▪ No immediate tangible benefits to RetailCo or MeatCo ▪ Developed prototype tool provides good starting point for RetailCo's IT development ▪ Reduced dependence on key account manager's expertise main benefit to MeatCo	▪ CandyCo's improved forecast accuracy has led to improved service towards RetailCo	▪ No immediate tangible benefits to RetailCo or ChemCo
Expected benefits if collaboration continued	▪ DairyCo hopes to achieve more efficient control of operations if successful in involving more of its major customers	▪ Both MeatCo and RetailCo are counting on opportunities to improve promotion decisions ▪ MeatCo expects to attain improved forecast accuracy in the future	-	-
Costs and investments during pilot phase	▪ No investments during pilot phase ▪ Pilot required significant amount of extra work from RetailCo's category manager and logistics planners	▪ No investments during pilot phase ▪ Pilot required moderate extra work from RetailCo's logistics planner	▪ No investments during pilot phase ▪ Pilot required moderate extra work from CandyCo's key account manager	▪ No investments during pilot phase ▪ Pilot required moderate extra work from ChemCo's key account manager
Expected costs and investments related to potential scale-up	▪ RetailCo's investment in forecasting personnel (original process) ▪ Moderate additional retailer labor (streamlined process) ▪ Investment in information sharing (sharing of POS data and forecasts) and potentially collaboration technology	▪ RetailCo's investment in improved management of promotion data ▪ Investment in information sharing (sharing of promotional data) and potentially collaboration technology (joint workspace) to reduce operative costs	▪ Investment in information sharing technology (efficient access to POS) to reduce operative costs	▪ Investment in information sharing technology (efficient access to POS) to reduce operative costs

Table 29. Relevance of the piloted collaboration practices.

	Case 1	Case 2	Case 3	Case 4
Relevance to retailer	Forecasting aspect of high priority (managing replenishment of fresh goods on a store level).	Both planning (more efficient promotions) and forecasting (estimating the impact on demand) aspects of high priority.	Moderate priority (no direct impact on retailer's own operations, but potentially enables more reliable supply from manufacturer).	Moderate priority (no direct impact on retailer's own operations, but potentially enables more reliable supply from manufacturer).
Relevance to manufacturer	Forecasting aspect of moderate priority. Information sharing and receiving binding decisions of high priority.	Forecasting aspect of moderate priority. Planning and monitoring aspect of high priority.	High priority	Low priority (due to supplier's difficulties in benefiting from access to demand data).

6.1.5 Conclusions

In relation to Question 3 examining the additional benefits and costs associated with deepening inter-company integration by moving from information sharing to collaborative forecasting, the study provides three observations:

Observation 1: The required investment in collaboration technology is not a key obstacle to large-scale forecasting collaboration.

Many articles present the lack of supporting technology or the high cost of the technology as important obstacles to forecasting collaboration (Fliedner, 2003; McCarthy and Golicic, 2002). Sometimes, technology is even presented as key to successful collaboration (Sherman, 1998). Based on the results of this study, however, it seems that the role of technology may have been overstated. As mentioned in the cross-case analysis, IT investments were considered necessary for scaling up each of the piloted collaboration approaches. Yet, none of the companies perceived the required IT investments as significant obstacles to collaboration. This leads to the conclusion that although the need for IT investments can slow down large-scale implementation of forecasting collaboration, it is unlikely to be the primary reason why some companies have decided not to engage in collaborative forecasting or have decided not to continue piloted collaboration practices.

Observation 2: Retailers' limited forecasting capabilities is a key obstacle to collaborative forecasting, but not to sharing of sales data or manufacturer-driven forecasting collaboration.

One of the cornerstones of forecasting collaboration and the CPFR process model is that the retailer actively participates in demand forecasting and that this improves the quality of the resulting forecast (see, for example, Aviv 2001; Aviv 2002, Raghunathan, 1999). However, of the four piloted collaboration practices examined in this study, the approach closest to CPFR and including the most active retailer involvement in forecasting was considered infeasible by the retailer. According to the retailer, scaling up the piloted collaboration would have required too heavy an investment in developing its forecasting capabilities and resources. Still, the retailer was able to implement and willing to scale up the more streamlined approaches tested in Case 2, Case 3, and Case 4.

If other retailers are in a similar situation as the case retailer, i.e. the retailers' forecasting resources and processes cannot support CPFR-style collaboration, this is likely to present an important, even the most important obstacle keeping retailers from adopting collaborative forecasting practices. Yet, retailer forecasting capabilities have to date not been discussed in the literature on collaborative forecasting (see, for example, Barratt, 2004; Barratt and Oliveira, 2001; McCarthy and Golicic).

As demonstrated by this case study, lack of forecasting capabilities does not impede more streamlined practices that focus on sharing of sales data (e.g. Case 3 and Case 4) and/or manufacturer-driven forecasting (Case 2).

Observation 3: Due to different planning horizons and aggregation levels, retailers and manufacturers have different forecasting and collaboration needs.

Another cornerstone of forecasting collaboration and CPFR is that both parties benefit from the collaboration. Yet, collaborative forecasting failed to improve forecasting performance in the cases studied. The only tangible performance improvement was attained in Case 3, which focused on sharing of sales data. In addition, none of the piloted collaboration practices examined were of equal relevance to both manufacturer and retailer. Due to retailers' significant power in European grocery supply chains (Hogarth-Scott and Parkinson, 1993), they typically benefit from high service levels and short replenishment lead-times even without collaborating with manufacturers. This is true for the case retailer, as well. This means that while manufacturers are most interested in getting the retailer to commit to firm plans earlier (to cope with long lead-times) and getting access to more accurate sales data (timely POS data, historical data on promotions) to be able to produce better forecasts, the retailer typically can work with less accurate forecasts (due to short lead-times) and its main problem is adequately managing store level demand, rather than aggregate demand. In such a situation, retailers' and manufacturers' different collaboration needs and priorities make it difficult to find collaboration practices that are of high relevance to both, which may be a reason why companies have found the implementation of collaborative forecasting so difficult.

Again, this is an observation that has not been presented previously in the literature on forecasting collaboration (see, for example, Barratt, 2004; Barratt and Oliveira, 2001; McCarthy and Golicic).

6.2 Retailer views on collaborative forecasting and sharing of sales data (Study 6)*

6.2.1 Purpose of the study

Study 6 provides answers to Question 3: What additional benefits and costs are associated with moving from sharing of downstream sales data to collaborative forecasting in supply chains?

More precisely, Study 6 was set up to investigate the generalizability of the observations made in Study 5 by examining a larger and more international sample of retailers. The examined observations are:

- Observation 1: The required investment in collaboration technology is not a key obstacle to large-scale forecasting collaboration.
- Observation 2: Retailers' limited forecasting capabilities is a key obstacle to forecasting collaboration based on comparison of forecasts (CPFR), but not to sharing of sales data or manufacturer-driven forecasting collaboration.
- Observation 3: Due to different planning horizons and aggregation levels, retailers and manufacturers have different forecasting and collaboration needs.

6.2.2 Methodology

The research approach employed in Study 6 is in-depth, structured interviews. Since the aim of the study was to investigate the generalizability of the observations made in Study 5, several retailers representing different countries were included. However, due to the detailed nature of the data needed as well as the lack of standardized terminology in the area of information sharing and forecasting collaboration, in-depth interviews were seen as a more reliable data collection tool than, for example, a postal survey, despite the limitations on sample size that it presents.

Sample

The sample of companies interviewed consists of twelve European grocery retailers. When contacting companies, the aim was to include leading retailers operating in different markets. The companies included in the study represent six regions: The Nordic countries, The UK, Northern Continental Europe, Western Continental Europe, Central Continental Europe, and Southern Continental Europe.

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*Results of this study have previously been presented in Småros, J., Angerer, A., Fernie, J., Toktay, B., Zotteri, G. (2004), "Retailer views on forecasting collaboration", Proceedings of the 9th annual LRN conference.

Another ambition when approaching the companies was to focus on leading European retailers, i.e. the companies most likely to have sophisticated supply chain management processes and development resources in place. Consequently, all of the interviewed companies are major players within the grocery sector. In fact, out of the twelve examined companies only two are outside of the top three (measured in market share) in their respective target markets.

The companies form a rather heterogeneous group with turnovers ranging from approximately 1 billion euros to over 20 billion euros. The study included:

- Six retailers with turnovers of less than 5 billion euros,
- Three retailers with turnovers of between 5 and 10 billion euros,
- Three retailers with turnovers of 10 billion euros or more.

Most of the companies operate several retail chains or store formats, ranging from small neighborhood stores to very large hypermarkets. However, it is important to note that no discounters are included in the study.

The companies also differ in private label penetration due to their different business strategies as well as the special characteristics of the target markets:

- Nine retailers have a private label penetration of below 20%,
- None of the retailers have a private label penetration of between 20 and 50%,
- Three of the retailers have a private label penetration of over 50%.

Finally, the companies differ in their involvement in forecasting collaboration:

- Three of the companies are currently involved in large-scale forecasting collaboration, i.e. have implemented permanent collaboration processes with several manufacturers,
- One has established permanent collaboration processes with a few manufacturers,
- Four of the companies are or have been involved in collaboration pilots, and
- Four of the companies did not mention being involved in any collaborative forecasting initiatives at all.

Data collection and analysis

Data was collected through in-depth structured interviews. The interviews were carried out by a team consisting of five researchers representing five universities and five different countries. This allowed for conducting the interviews in the respondents native languages.

A total of twenty-one persons participated in the interviews, some of which were interviewed several times. The group of interviewees consisted mainly of directors and managers in charge of logistics, supply chain management, purchasing, IT or development.

The interview questionnaire was designed to solicit and capture information regarding key performance indicators, the companies' logistics processes, manufacturer collaboration, and logistics-related challenges and opportunities. The questionnaire was first tested on one of the respondents. After this, it was slightly revised (see Appendix IV for the final version of the questionnaire).

Based on the interviews, company-specific case reports were compiled. These reports were checked first by the members of the research team and then by the interviewees. The data collection effort lasted from August 2003 to June 2004.

Due to the limited sample size and the nature of the data collected, data analysis was qualitative in nature. The companies' processes, performance data, experiences and opinions were compared in view of the observations made in Study 5. Special attention was paid to the differences between the retailers that have already implemented large-scale forecasting collaboration with manufacturers and the retailers who have to date only been involved in small-scale implementations, pilots, or no collaboration efforts at all.

6.2.3 Role of collaboration technology (Observation 1)

Use of collaboration technology in large-scale implementations

In the study, three retailers engaged in permanent forecasting collaboration with several manufacturers were encountered. In the following sections, we will refer to these instances as Large-scale implementations 1 – 3 (see Table 30).

Table 30. The three large-scale implementations of collaborative forecasting encountered in Study 6.

	Content of collaboration	Scale
Large-scale implementation 1 (LS1)	Checking of forecasts for events with store managers and manufacturers.	All major manufacturers.
Large-scale implementation 2 (LS2)	Joint forecasting of promotions, monitoring of realized demand.	All manufacturers, more focus on manufacturers of defined key value items.
Large-scale implementation 3 (LS3)	Manufacturer-driven CPFR.	10 top international manufacturers, plans to roll out to all major manufacturers.

The first one of these implementations (LS1) focuses on events, i.e. promotions, seasons and other situations of changing demand. The retailer's central organization first produces an initial forecast using forecasting tools. The forecast is then checked by the store managers and the manufacturer of the product. Since there are many store-specific factors having an impact on how, for example, a promotion works in a specific store, the resulting forecast is only used by the retailer to manage the first days of an event – when a few days of sales data are available the individual stores' forecasts are rapidly updated based on realized sales.

The second large-scale implementation (LS2) focuses on promotions. It is restricted to the retailer–manufacturer interface and includes more IT support than the first one. The retailer has implemented an exchange-based solution that enables it to collaboratively develop forecasts for promoted products with all major manufacturers. This is how it works: Twelve weeks before going live, manufacturer representatives and the retailer's buyers agree on the level of the promotion and enter it into the system. Three weeks later this information is converted into case quantities to meet logistics requirements. By the last four weeks these data are incorporated into the automated forecasting system and monitored. Through the system, manufacturers get access to sales data and availability information, which makes it possible to monitor and evaluate whether the promotion is having the expected impact on demand. The system also provides the retailer and the manufacturers with warnings when there are deviations from the plan.

The third large-scale collaboration (LS3) is a manufacturer-driven version of the CPFR process model. The retailer's business units first develop forecasts for their products. The forecasts are divided into "normal" (based on trend forecasting) and "seasonal" (to account for Christmas, different kinds of events etc.). Through the CPFR software, which is implemented as part of a private exchange, manufacturers can examine these forecasts, pick up trends, and identify exceptions compared with their own forecasts. The identified exceptions are either handled automatically or manually by the retailer.

Table 31. Collaboration technology used in the large-scale implementations of collaborative forecasting.

	Collaboration technology employed
Large-scale implementation 1	No special collaboration technology.
Large-scale implementation 2	Exchange-based solution enabling retailer and manufacturers to collaboratively develop forecasts. Automatic warnings when there are deviations from the forecast.
Large-scale implementation 3	Private exchange enabling manufacturers to review forecasts. Retailer's handling of exceptions partly automated.

Role of technology as viewed by retailers lacking large-scale implementations

When discussing collaborative forecasting with the retailers, technology issues rarely came up. The following observations concerning the role of IT were made:

> *"Sure, IT helps, but it's the time investment that is heavy."* (Retailer that is involved in a collaboration pilot with one manufacturer.)

> *"We constantly make and plan IT investments to improve our own processes. Although many of these investments are important for future collaboration, they are primarily made in order to improve our own efficiency."* (Retailer that has tested several different collaboration approaches with different manufacturers.)

> *"We need to get our internal systems in order first."* (Retailer that is involved in a collaboration pilot with one manufacturer.)

Results

The fact that retailers did not mention collaboration technology as a major inhibitor or enabler of forecasting collaboration in addition to the evidence on how companies have been able to implement large-scale collaboration with available tools, supports the observation that investments in collaboration technology do not present a primary, or even a very critical obstacle to implementation of large-scale forecasting collaboration.

6.2.4 Role of retailers' forecasting capabilities (Observation 2)

Retailers' forecasting processes

In order to investigate Observation 2, we return to the three large-scale implementations identified earlier and examine the forecasting processes of the retailers involved in them (see Table 32). The retailer involved in the first large-scale implementation (LS1) uses a rather sophisticated forecasting approach: past sales history is used to determine the number of customers that are going to enter a store and another algorithm analyses the number of units sold per customer. For events, e.g. promotions, multivariate regression taking into account variables such as the features of the promotion or the weather is used to predict the promotional lift per customer. The retailer involved in the second large-scale implementation (LS2) also emphasizes the importance of forecasting and has eighty forecasters allocated to the business units managing the different product categories. The retailer involved in the third large-scale implementation (LS3) – the only large-scale implementation resembling the CPFR process model – has also invested in forecasting capabilities. The collaboration is based on the retailer providing system-generated forecasts for manufacturers to examine and compare with their own forecasts. The majority of identified exceptions are handled automatically by the retailer, but a significant number of the exceptions are still checked manually.

Table 32. Forecasting tools and resources of the retailers involved in large-scale implementations of collaborative forecasting.

	Retailer's forecasting resources
Large-scale implementation 1	Advanced forecasting tools*.
Large-scale implementation 2	Advanced forecasting tools*, forecasting staff.
Large-scale implementation 3	Advanced forecasting tools*, staff for handling exceptions generated by the collaboration process.

*"Advanced forecasting tools" here refers to tools with features beyond simple time-series forecasting, such as multivariate regression.

The other interviewed retailers are different from these three companies. The majority of retailers employ very basic time-series based forecasting tools. Only one company is currently implementing a more powerful system. Furthermore, none of the other companies have dedicated forecasting staff.

Sharing of sales data

When examining the retailers' willingness to engage in other kinds of collaboration with manufacturers, it can be noticed that all of the retailers share sales data with manufacturers (Table 33). However, a great deal of this information sharing is somewhat ad hoc in nature, related to specific temporary development projects and there is little IT support for it – e-mail and spreadsheet programs are the main tools.

When manufacturers are systematically given access to sales data, it is usually part of some kind of VMI arrangement in which the manufacturer monitors the retailer's inventory levels and sales and suggests or automatically sends replenishments. (The retailers interviewed also used the terms co-managed inventory (CMI) and just-in-time delivery (JIT) for this type of arrangement). Of the twelve companies interviewed, seven have such arrangements; in five of these, sell-through data from the retailers' distribution centers are exchanged, in two POS data is made available to the manufacturers.

In addition, three companies share POS data with manufacturers in a systematic way, but without much IT support. Two use spreadsheet programs and e-mail for communication. One of the two shares sales data with all of its manufacturers on a monthly basis, as well as some information on product availability and spoilage. The other retailer frequently shares POS data on newly introduced products with manufacturers to enable the manufacturers to rapidly update their forecasts for these products. A third retailer also shares sales data on paper, but never in electronic form as it is concerned about data leakage.

Although some retailers are planning to give manufacturers access to data and invest in IT solutions to support efficient information sharing, only two retailers in the sample currently have systems in place to enable rapid and efficient information sharing with all or the majority of their suppliers. They share data on sales, margins and the like with manufacturers on a daily basis (the data is actually updated several times a day) using electronic exchanges. In addition, one of the retailers has a rather unique arrangement with vertically integrated manufacturers. It offers them full access to the data in its enterprise resource planning system, which makes it possible for the manufacturers to examine, among other things, their products' turnovers in the stores.

Table 33. Sharing of sales data with manufacturers.

Sharing of sales data	Number of retailers
Ad hoc information exchange	All retailers
Systematic information sharing without IT support	Three retailers
Systematic information sharing with IT support	Two retailers + seven retailers sharing sell-through or POS data with VMI partners
IT integration	One retailer

Results

Based on the interviews, it can be concluded that most retailers do, indeed, lack dedicated forecasting resources and that their forecasting tools often are rather simple. The retailers involved in large-scale collaboration are all exceptional in that they have more advanced forecasting tools than the other retailers in the sample. In some cases they also have dedicated forecasting personnel. These observations support the notion that large-scale forecasting collaboration requires forecasting capabilities that most retailers, even leading ones, currently do not have.

An interesting observation that is slightly different from, although not contradictory to Observation 2 is the emphasis on retailer forecasting tools and data (for generating forecasts) rather than on explicit forecasting resources (for reviewing and adjusting the forecasts). This is probably the result of the implementations found in the companies generally being rather streamlined and more focused on information sharing (sharing of system-generated forecasts) than on actually developing forecasts in co-operation with manufacturers. Even the most CPFR-like process (LS3) is rather manufacturer-driven, giving manufacturers most of the responsibility for controlling forecast quality.

The results also support the second part of Observation 2 by demonstrating that also companies that lack advanced forecasting processes, tools, and resources, can engage in sharing of sales data. However, it seems that sales data is often shared within the context of some kind of replenishment collaboration in which the manufacturers take responsibility for replenishing the retailer's inventory.

6.2.5 Retailers' forecasting and collaboration needs (Observation 3)

When examining the order-to-delivery lead-times between manufacturers and retail distribution centers, it can be noted that the orders are typically filled within 48 hours, with a median value of about 20 hours for the companies in the sample. The reported average order-to-delivery cycles range from about 14 hours to 48 hours. The lead-times for fresh goods tend to be significantly shorter with a median value of about 14 hours and ranging from about 12 to 30 hours. For other product types, the median value is 48 hours, ranging from 32 to 168 hours. For imports and specialty goods, lead-times can be anything between 1 and 100 days.

The order-to-delivery lead-times between distribution centers and stores are slightly shorter on average. The median value of the reported average lead-times for fresh goods is 24 hours, ranging from 14 to 32 hours. For other goods, the median value is about 34 hours, ranging from about 15 to 48 hours. The median of the average lead-times for all products reported by the companies is 32 hours, ranging from about 14 to over 32 hours. Several retailers pointed out that the order-to-delivery lead-times to stores do not necessarily give an accurate picture of reality. In practice, lead-times are not only determined by the time it takes to handle the order and pick and ship the goods, but in essence a function of the delivery frequency to the stores.

The service levels from manufacturers to distribution centers and from distribution centers towards the stores are both quite high on average (Table 34). Yet, several of the companies interviewed stated that they are not satisfied with the manufacturers' service levels. In many of these cases, the companies are satisfied with the overall level, but not with the service levels offered by certain manufacturers or in certain situations. Most difficulties are related to non-food products and situations, such as promotions, with high demand uncertainty. Some of the companies also mentioned that competitor activities (e.g. big promotions by other retailers) sometimes affect the manufacturers' service levels towards them. In addition, two companies, rather surprisingly, stated that they find it difficult to get good service from the larger manufacturers.

The service level from the distribution centers to the stores is, in general, considered to be better than that of the manufacturers. One of the retailers estimated that out of the distribution centers' delivery problems only 5% were caused by the distribution center and

95% by manufacturer stock-outs. However, also here, promotions and other situations in which demand forecasts are critical are considered problematic. In addition, some retailers mentioned problems with execution, i.e. picking errors and transportation-related problems.

Table 34. Service levels in the retailers' supply chains.

	Manufacturer to distribution center	Distribution center to store
Median service level	98 %	98 %
Max service level	98 %	99 %
Min service level	95 %	97 %

Results

The collected data verify that lead-times are, indeed, short and service levels high, both for companies who do collaborate and for companies who do not collaborate. Due to the short lead-times and high service levels, the retailers do not have the same forecasting needs as suppliers, especially on an aggregate level, just as suggested by Observation 3. Rather than investing in attaining a very high forecast accuracy, the retailers can, in many cases, rely on the responsiveness of their supply chains. One retailer even commented as follows:

> *"When we forecast demand for a given promotion we know that even if during the week demand is 50% above or 50% below expectation we can recover given our flexibility. So, we measure our forecast accuracy in terms of frequency of accuracy for the week below 50%."*

Interestingly, this retailer is one of the companies involved in forecasting collaboration with manufacturers.

When digging deeper into the data, potential reasons why some companies invest in forecasting and collaboration despite the already high service levels and short lead-times emerge. There is some indication that the companies that have the most developed automatic store ordering systems (i.e. systems that cope or are being developed to cope with not only stable demand but also events, such as promotions and important seasons) and are following a centralized approach to managing store replenishment (i.e. replenishment methods and parameters are set by the retailer's central organization) have invested or are investing in forecasting tools. These companies also seem to be most interested in forecasting collaboration.

6.2.6 Conclusions

In relation to Question 3 concerning the additional benefits and costs of collaborative forecasting in comparison to sharing of sales data, the study supports the generalizability of the observations made in Study 5:

Observation 1: The required investment in collaboration technology is not a key obstacle to large-scale forecasting collaboration.

Three instances of large-scale forecasting collaboration were encountered in Study 6. Of these three, two build on rather extensive IT support (LS2 and LS3) including private exchanges and tools for dealing with exceptions automatically. However, one of the implementations (LS1) can be considered low-tech, as it does not use any specific collaboration tools. These observations support the findings of Study 5 indicating that the required investment in collaboration technology does not present a key obstacle to large-scale forecasting collaboration, contrary to what has been argued in some of the literature on forecasting collaboration (see, for example, Fliedner, 2003; McCarthy and Golicic, 2002; Sherman, 1998). Furthermore, when discussing collaborative forecasting with retailers lacking large-scale implementations of collaborative forecasting, technology issues rarely came up, suggesting that the role of IT is not perceived to be critical.

Observation 2: Retailers' limited forecasting capabilities is a key obstacle to forecasting collaboration based on comparison of forecasts (CPFR), but not to sharing of sales data or manufacturer-driven forecasting collaboration.

Based on the interviews conducted it can be concluded that retailers typically lack dedicated forecasting resources and that their forecasting tools are often rather simple. The retailers involved in large-scale collaboration are exceptional in that employ more advanced forecasting tools than the other retailers. In some cases, they also have forecasting personnel. These observations support the finding of Study 5 that successful large-scale forecasting collaboration requires forecasting capabilities that most retailers, even leading ones, currently do not have. This is interesting, since it has to date not been discussed in the literature on forecasting collaboration (see, for example, Barratt, 2004; Barratt and Oliveira, 2001; McCarthy and Golicic, 2002) and presents a striking contrast to the assumptions of, for example, Raghunathan (1999) and Aviv (2001; 2002) who build their analytical models on the premise that retailers are able to provide accurate and reliable forecasts that when shared with manufacturers improve supply chain efficiency.

An interesting observation that is slightly different from, although not contradictory to Observation 2 is the emphasis on retailer forecasting tools and data (for generating forecasts) rather than on explicit forecasting resources (for reviewing and adjusting the forecasts). This is probably due to the implementations identified in the examined companies generally being rather streamlined and more focused on information sharing (sharing of system-generated forecasts) than on actually developing forecasts in co-operation with manufacturers. Even the most CPFR-like process (LS3) is rather manufacturer-driven, giving manufacturers most of the responsibility for controlling forecast quality.

The results support the second part of Observation 2 by demonstrating that also companies that lack advanced forecasting processes, tools, and resources can engage in sharing of sales data, something that virtually all companies did, in one way or another. However, an interesting observation is that it appears that sharing of sales data often takes place in the context of replenishment collaboration. This suggests that the manufacturers provide the retailers with an incentive to share information by taking responsibility for controlling their inventories.

Observation 3: Due to different planning horizons and aggregation levels, retailers and manufacturers have different forecasting and collaboration needs.

The collected data verify that lead-times are, indeed, short and service levels high, both for companies who do collaborate and for companies who do not collaborate. Due to the short lead-times and high service levels, retailers do not have the same forecasting needs as suppliers, especially on an aggregate level, just as suggested by Observation 3. Rather than investing in attaining a very high forecast accuracy, the retailers can, in many cases, rely on the responsiveness of their supply chains.

Yet, some of the companies have chosen to invest in developing their forecasting capabilities. There is some indication that the companies that have the most developed automatic store ordering systems and are following a centralized approach to managing store replenishment are investing in forecasting tools. This, however, is a rather speculative observation at this point and needs to be further examined.

7 CONCLUSIONS

7.1 Situational factors affecting the value of manufacturer access to downstream sales data

This section presents conclusions related to Question 1:

In what situations does sharing of downstream sales data with upstream supply chain members enable increased efficiency?

Demand signals passing through supply chains are subject to different kinds of distortion. In Studies 1 and 2, two kinds of distortion were identified: 1. Increase in demand variability, and 2. Delay in demand synchronization. The increase in demand variability is a well-known phenomenon and has been documented in many studies (see, for example, Forrester, 1961; Fransoo and Wouters, 2000). The delay in demand synchronization has, however, not been systematically examined before. Both types of distortion can, as shown by Studies 1 and 2, be caused by batching in supply chains. On the one hand, batching makes demand increasingly lumpy, which increases demand variability and causes random peaks and valleys in demand. This has been observed by several authors, perhaps most notably by Burbidge (1989). On the other hand, batching also increases the time it takes to convey a change in demand. If there is significant batching in the supply chain, in the form of high inventories or large minimum order quantities, it takes more time to accumulate enough demand to generate an order, which slows down progress of the demand signal in the supply chain. The increase in demand variability can be observed both in situations of stationary demand and situations of transient demand, whereas delay in demand synchronization is only relevant in situations of transient demand. Both types of demand distortion make it more difficult to efficiently control production and inventories upstream in the supply chain and increase the risk of overreacting to perceived changes in demand.

Studies 1 and 2 show that sharing of downstream sales data with upstream supply chain members is of very different value for different products. Since one main cause of demand distortion is batching, sharing of downstream sales data is more valuable for products with low replenishment frequencies, i.e. typically slow-moving, so-called C-products. For fast-moving A-products with frequent replenishments and small batch sizes relative to their average demand, demand distortion is less of a problem and the difference between manufacturer order data and downstream sales data much smaller, hence reducing the value of information sharing. Studies 1 and 2 demonstrate that this holds true both in the case of mature products, which mainly suffer from increasing demand variability, and for recently introduced products, which are subject to delay in demand synchronization.

Manufacturer access to downstream sales data even from a fraction of their customers can reduce the problem of demand distortion, as shown by Studies 1 and 3. Study 1 uses simulation to examine a situation of stationary demand and shows how the manufacturer's benefits, i.e. more level demand and, thus, more efficient inventory and capacity management, increase when it gets access to sell-through data from more and more customers. However, it also demonstrates that notable benefits can be attained already when a minority – one third of the customers – shares its sales data with the manufacturer. Study 3 empirically examines product introductions and presents a similar conclusion; access to POS data from even one key customer can help the manufacturer to produce more accurate forecasts of its total demand and, in this way, to better manage production and secure its material supply.

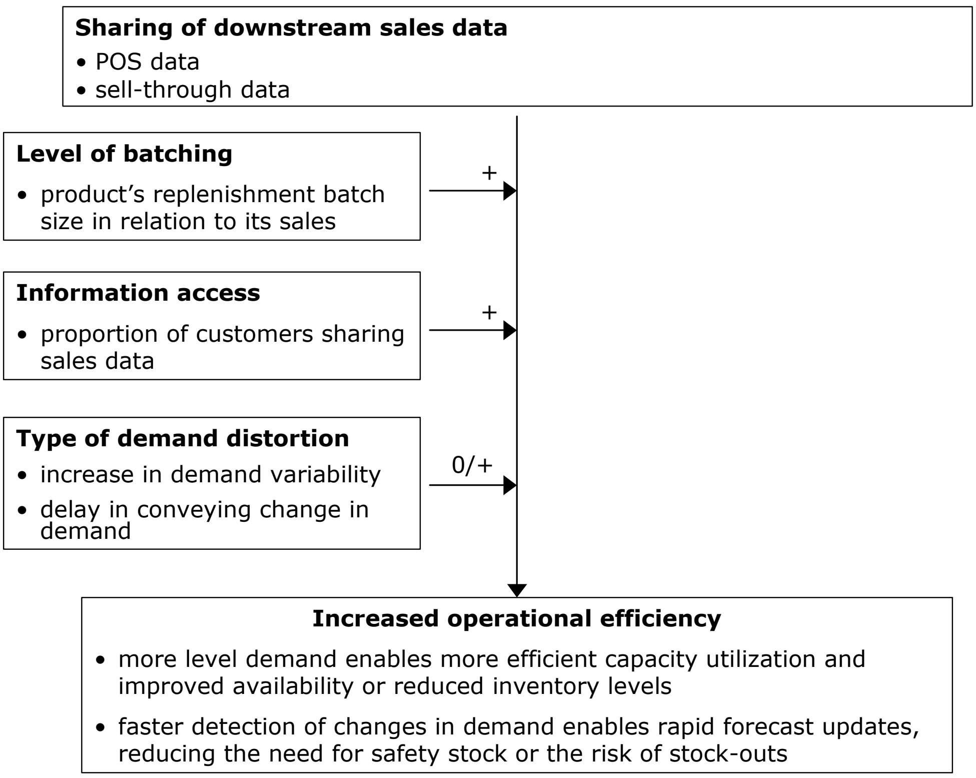

Figure 22. Situational factors impacting on the value of sharing of downstream sales data with upstream members in supply chains.

However, Study 2 also demonstrates that the different echelons of a supply chain may distort the demand signal in different ways. In the supply chain setting studied in Study 2, variability was mainly induced by the distributors but delay in demand synchronization was induced both by the retail outlets and the distributors. In the studied supply chain, this means that in order to remedy delay in demand synchronization for recently introduced products, POS data is typically needed; sell-through data still contains a significant delay. On the other hand, to remedy the increase in demand variability, sell-through data is often sufficient and POS data does not add much value. This finding is further supported by Study 3 in which the case companies were unwilling to invest in sharing and analyzing POS data for mature products with stable demand. For these products they considered the sell-through data available through their VMI arrangements sufficiently accurate. These observations highlight the need for measuring the distorting impact of the different echelons when designing information-sharing efforts to ensure that the appropriate kind of demand information is used.

7.2 Prerequisites for manufacturers to benefit from access to downstream sales data

This section presents conclusions related to Question 2:

What are the prerequisites for upstream supply chain members to be able to benefit from access to downstream sales data?

Studies 1 and 3 show that a <u>manufacturer's production planning and purchasing cycles have an important impact on the value of access to downstream sales data</u> both for products with stable demand and for products with changing demand. Study 1 shows that, in a situation of stable demand, when the manufacturer's production planning cycle is long, the variability of demand is typically averaged out during the production planning period. This means that the need for and value of more accurate sales data, such as distributor sell-through data, is significantly reduced. On the other hand, Study 1 also shows that access to downstream sales data may enable a manufacturer to move to a shorter production planning cycle without having to face the negative effects of increased demand variability. Study 3 further shows that if production or purchasing decisions are made infrequently, e.g. due to an aspiration to achieve long production runs, to attain long freeze periods in production, or to buy raw materials or packaging materials in large batches, the value of manufacturer access to downstream sales data in transient situations is reduced. In these situations, the manufacturer needs to prepare for the change in demand by creating a sufficient buffer stock to minimize the risk of stock-outs while waiting for the next opportunity to produce or order more goods. If it takes a long time before the next production run takes place, demand synchronization will already have taken place when the order decision is made, reducing the value of access to downstream sales data.

As shown by Studies 1 and 2, the attainable benefits of manufacturer access to downstream sales data also depend on how the data are used. Study 1 shows that <u>in a situation of stable demand, directly loading the manufacturer's production with downstream sales data rather than customer orders can be beneficial</u> if it its technically feasible from the point of view of the manufacturer's enterprise resource planning system. In a situation of transient demand, simple loading of the manufacturer's production with

POS data can, however, as shown by Study 2, actually increase the manufacturer's inventories. As shown by Study 3, in transient situations, manufacturers can use POS data to update forecasts and, in this way, control inventories and purchasing of materials. In addition, the results of Study 2 suggests that POS data in transient situations may be used for production loading purposes, provided that the delay in demand synchronization is taken into consideration.

The manufacturer's forecasting process and level of internal integration also have an impact on the realized value of information sharing. As shown by Study 3, if forecasting does not take place on a customer level, it can be difficult to use downstream sales data available from only part of the customer base. In addition, if the data needs to be manually reviewed and interpreted in some way - if it is not, for example, reliable as it is, if manual interpretation is needed to turn the data into a forecast, or if it is possible to produce more general conclusions based on manual review of the data - the involvement of key account managers or other sales representatives with customer and market knowledge in the information sharing effort is essential. It is also important that the information produced by these experts is actually used in production, i.e. that there is a sufficient level of integration between sales and operations.

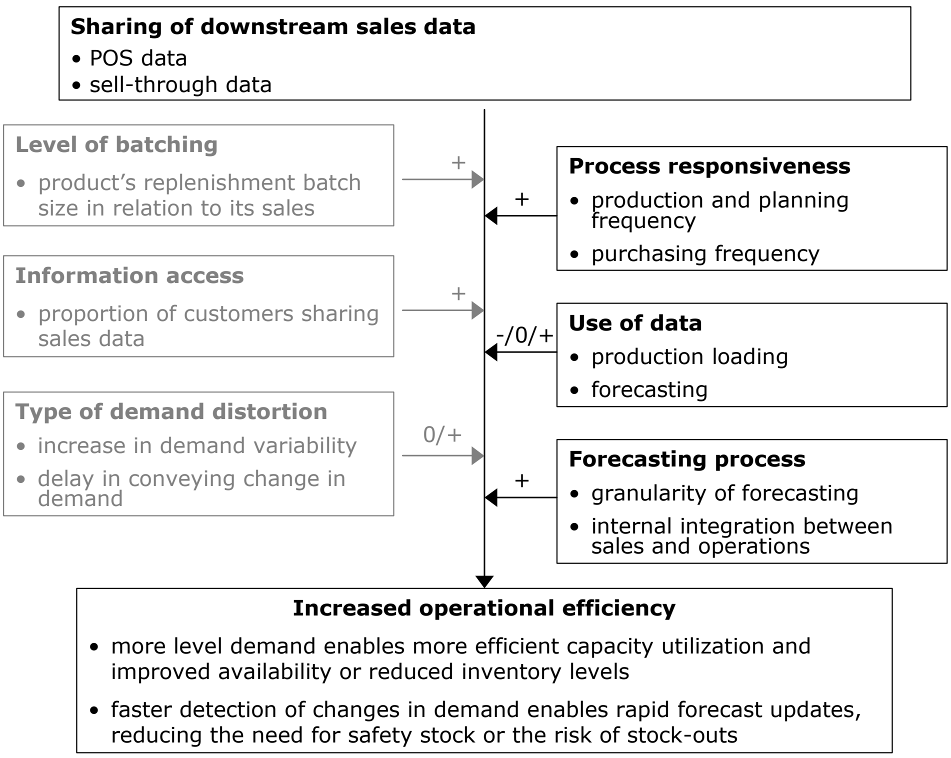

Figure 23. Manufacturer's prerequisites for being able to access to downstream sales data.

7.3 Additional costs and benefits of collaborative forecasting

This section presents conclusions related to Question 3:

> *What additional benefits and costs are associated with moving from sharing of downstream sales data to collaborative forecasting in supply chains?*

The suggested value of collaborative forecasting is based on the assumption that the quality of the upstream members' forecasts will be improved through the collaboration. However, Study 4 shows that this assumption does not necessarily hold. In the case examined in Study 4, the retailer's forecast was systematically poorer than the manufacturer's, especially for recently introduced products and products approaching the end of their life-cycle. Giving the manufacturer access to the retailer's forecast would, therefore, not have improved the quality of the manufacturer's forecast. Study 5, involving a different retailer, provided similar results: two of the development projects examined in Study 5 included retailer involvement in forecasting, however, in neither of these cases did the manufacturer's forecasting performance improve as a consequence. Study 6 shows that grocery retailers' lack of forecasting capabilities is a more general phenomenon: most European grocery retailers currently rely on simple time-series forecasts. In such a situation, the added value of manufacturers getting access to retailers' forecasts is clearly very limited.

The reason why retailers typically have poorer forecasting tools and processes than manufacturers is the difference in retailer and manufacturer forecasting needs. Manufacturers typically need to plan weeks, even months ahead to secure availability of raw materials and packaging materials and to attain efficient capacity utilization in production. Most retailers, on the other hand, have rather limited forecasting needs due to relatively responsive (lead-times of days rather than weeks) and reliable (typical availability levels over 97%) supply chains. This also means that many retailers currently have limited incentives to invest in forecasting collaboration since they do not need to improve their own medium-term, aggregate-level forecasting performance. Although many retailers are developing forecasting capabilities, their main goal is typically to improve short-term, store-level forecasting, rather than aggregate-level, medium-term forecasting, which would be of interest to the manufacturers.

Although it is clear that retailers have limited incentives to share forecasts, this also applies to sharing of sales data, which, too, is likely to benefit the manufacturers more than the retailers. Yet, as shown by Study 6, many retailers share sales data with manufacturers. One reason behind the retailers' greater willingness to share sales data rather than forecasts seems to be that retailers often share sales data as a part of a replenishment collaboration in which the manufacturer assumes responsibility for replenishing the retailer's inventory. The manufacturers, thus, reward collaborative retailers by doing some of the work for them and by guaranteeing product availability, i.e. they provide additional incentives for the retailers to share data. On the contrary, manufacturers to date have not been willing to offer additional incentives, such as improved trade terms or availability guarantees, to retailers who share forecasts.

The retailers' greater unwillingness to share forecast information compared with sharing of sales data is also explained by the higher costs involved. Several sources have suggested that the required investments in collaboration technology present an important, even the most important obstacle to forecasting collaboration (Fliedner, 2003; McCarthy and Golicic, 2002; Sherman, 1998). Based on Studies 5 and 6, it can be concluded that investment in collaboration technology, such as web-based electronic exchanges, may slow down large-scale collaboration, but that it does not form a critical obstacle to collaboration or a reason for companies not to collaborate. The companies involved in Study 5 considered IT investments to be necessary for scaling up each of the piloted collaboration approaches. Yet, none of the companies considered the required IT investments as significant obstacles to collaboration. In Study 6, it was found that large-scale collaboration is, in fact, possible without significant investments in special collaboration technology. On the other hand, companies have also been able to implement large-scale, more complex collaboration processes using special collaboration technology. On a general level, technology was not given a major role either as an enabler or an inhibitor by the majority of companies interviewed.

In fact, the lack of forecasting tools and resources seems to be the major obstacle to sharing of forecast information, from the retailers' point of view. Although several retailers are planning to take into use more advanced forecasting tools, few retailers currently have the tools or resources to support sharing of forecasts. In Study 5, the lack of forecasting resources was the main reason why the case retailer was unwilling to scale up one of the piloted collaboration practices. In Study 6, the companies involved in large-scale forecasting collaboration were companies who had already invested in developing forecasting capabilities. Several of the companies currently not involved in forecasting collaboration explained that producing and reviewing forecasts was too laborious compared with the attainable benefits. The willingness to collaborate, thus, seems to be very tightly linked to the retailers' forecasting capability – if a retailer already has forecasting tools and resources in place, the additional cost of collaborating becomes manageable, similarly to the case of sharing sales data. However, if these components are lacking, the cost of implementing them just for the sake of supporting collaboration is generally considered too high in relation to the attainable benefits.

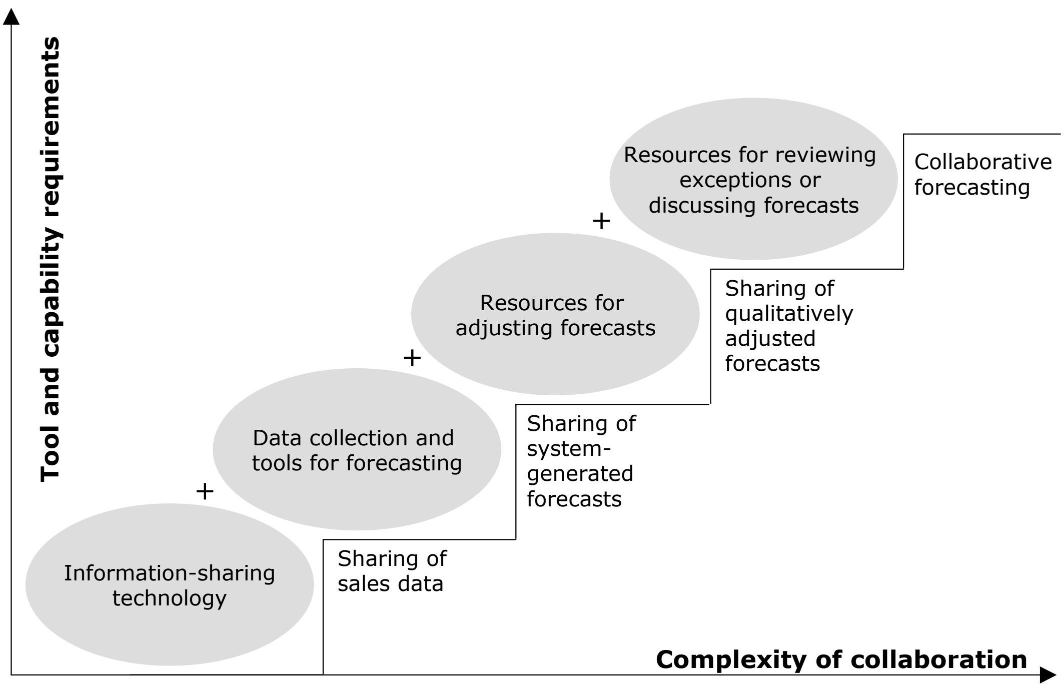

Figure 24. Required retailer capabilities, investments and costs related to different levels of information sharing.

Finally, although at this point still a rather tentative finding, it seems that collaboration based on comparing of forecasts may not be a key goal even for the manufacturers. The manufacturers involved in the collaboration projects examined in Study 5 stated that their most important collaboration needs were: 1. To receive binding plans concerning, for example, retailer promotions at an earlier stage, and 2. To get access to more accurate sales data, such as timely POS data for product introductions and historical POS data on promotions, for forecasting purposes. There is, thus, some indication that many manufacturers have seen the CPFR movement as an opportunity to get access to better demand data and increased retailer commitment to plans, rather than to more accurate forecasts, and that this may be the main reason why they have been quick to embrace CPFR although the benefits of comparing forecasts may be marginal.

Though tentative, this finding seems to be supported by the results of the studies presented in this thesis. The results of Studies 1 and 2 indicate that for mature products that are not subject to promotions or seasonality, manufacturer access to distributor sell-through data remedies most of the problems related to demand signal distortion in the supply chain. In these situations, forecasting collaboration is unlikely to bring significant benefits. For products with changing demand, such as recently introduced products, the results of Studies 3 and 4 indicate that the manufacturer can benefit more from access to POS data that enables it to rapidly update its forecasts than from access to retailer forecasts. Finally, in situations of demand peaks that manufacturers need to prepare for in advance, such as promotions, the results of Study 5 show that forecasting collaboration does not necessarily improve forecast accuracy if the retailer lacks the necessary forecasting capabilities. However, manufacturer access to historical POS data on past promotions in a specific product category may enable improved forecast accuracy.

8 DISCUSSION AND SUGGESTIONS FOR FURTHER RESEARCH

8.1 Sharing of downstream sales data

Information sharing in supply chains has been subject to much research during the last decade. The research method of choice has, with few exceptions, been analytical modeling. This is perhaps why a majority of the research has focused on situations of stationary demand or auto-regressive demand (cf. Gavirneni et al, 1999; Chen 1998; Aviv and Federgruen, 1998), although many authors have suggested that information sharing could be more valuable in situations of irregular, changing demand (cf. Cachon and Fisher, 2000; Lee et al., 2000).

The main contribution of this thesis in the area of information sharing is its examination of demand signal distortion and the value of information sharing in the context of product introductions. By introducing the metrics of bias and delay in demand synchronization, this work provides some initial tools for understanding information distortion beyond the well-known phenomenon of demand variability amplification. These metrics should, however, be considered works-in-progress. Empirical research is needed to establish their validity. The metrics also need to be further developed for increased accuracy. Currently, for example, fluctuations in bias make it difficult to attain reliable readings, especially for low values of bias.

The first results of the use of these tools are, however, intriguing: although batching seems to be a main cause of both delay in demand synchronization and of variability amplification, the different echelons of the supply chain seem to induce variability and delay to different extents. The accuracy and value of, for example, sell-through data and POS data, can thus be different in different situations and different supply chains. This observation merits further research. Empirical research examining what happens to the demand signal in actual supply chains would increase our understanding of where delay typically originates in. In addition, analytical modeling could be useful for increasing our understanding of the exact relationship between bias, delay in demand synchronization, and order batching. The statistical analyses of simulation results presented in this thesis were inconclusive on this point.

In addition, simulation results indicate that the inventory initializations made in the channel-fill stage of a product launch have an important impact on the magnitude of the bias and the delay in demand synchronization. In fact, the results suggests that by making informed choices concerning the initial stock levels, companies could be able to significantly reduce the problem of demand signal distortion in the context of product introductions even without information sharing. If this conclusion can be shown to be correct and the logic for setting the initial inventory values can be established, e.g. using methods from the field of control engineering or system analysis, it can have great practical implications.

This work also contributes by examining contingency factors affecting the attainable benefits of information sharing both in situations of stable demand and in the context of product introductions.

Although research indicates that the manufacturers should receive all or the majority of the benefits of information sharing (cf. Raghunathan. 1999; Yu et al., 2001), many manufacturers have found in difficult to benefit from information-sharing practices (Lapide, 2001; Vergin and Barr, 1999). Yet, little research examining the reasons behind these difficulties has been conducted. This thesis presents several contingency factors that have an impact on the value of information sharing. It is shown that a manufacturer's forecasting process and level of internal integration are of great importance to how it is able to use POS data in managing product introductions. In addition, the studies suggest that the way that the downstream sales data is inserted into the manufacturer's IT systems or used for production and inventory control purposes impacts on the attainable benefits.

Furthermore, the research presents an interesting factor affecting the attainable benefits of information sharing: the manufacturer's production planning frequency. Through simulation and case research it is shown that a lower production planning frequency reduces the benefits of access to downstream sales data in managing product introductions and the importance of access to downstream sales data for mature products. This is a new and interesting observation. If the observation is correct, it means that multinational companies with their focused production plants and typically infrequent production runs are in a worse position to benefit from information sharing than more agile, local manufacturers. On a more general level, this observation also highlights the importance of taking into account the supply chain members' decision-making frequency when measuring the bullwhip effect in supply chains and gives rise to the following question: How much of the bullwhip effect is, in fact, "academic" in the sense that it is observed in bullwhip calculations but is of little practical relevance in the supply chains where it is observed?

The research also examines the impact of replenishment frequency on the value of information sharing. Using simulation and actual supply chain data, the research reaches the same conclusion as Kaipia et al. (2002) with their analytical model: manufacturer access to downstream sales data is not equally valuable for all products, rather it is more valuable for products with large replenishment batch sizes compared to their average demand. The research also adds to the work of Cachon and Fisher (2000) by further explaining the relationship between replenishment frequency and the value of sharing of sales data.

In this thesis, information sharing has been examined only in the retailer-manufacturer interface. Additional research is needed to establish whether sharing of sales data can be of value further upstream in the supply chain, e.g. between manufacturers and their suppliers, or whether other forms of collaboration are more relevant.

8.2 Collaborative forecasting

As indicated by the literature review, there is not much previous research on the topic of collaborative forecasting. However, the literature that can be found is quite unanimous of its support of the concept (see, for example, Barratt and Oliveira, 2001; Lee et al. 1997b; Zhao et al., 2002). Some authors even propose universal retailer adoption of the concept (Raghunathan, 2001). Interestingly, despite the enormous hype triggered by the introduction of the CPFR process model in the late 1990's and numerous roadmaps and implementation guides made available by organizations such as ECR Europe and the VICS association, companies have been slow to adopt collaborative forecasting practices, pilot implementation have failed to lead to large-scale implementations, and CPFR seems to be losing momentum (Barratt, 2004; Corsten, 2003; Sliwa 2002). Although a few empirical studies have put forth inhibitors that may explain this slow take-up (Barratt, 2004; Barratt and Oliveira, 2001; McCarthy and Golicic, 2002), it is currently unclear whether the problems experienced by companies are more general in nature, e.g. lack of trust or lack of shared goals, or specific to the concept of collaborative forecasting.

The main contribution of this thesis in the area of forecasting collaboration is that it, based on empirical research, challenges some basic assumptions of collaborative forecasting in the grocery sector. Firstly, it is shown that retailers involved in large-scale collaboration can be considered exceptional in the sense that they have invested in sophisticated forecasting tools and, in some cases, even in dedicated forecasting personnel, whereas the majority of retailers currently lack the forecasting capabilities needed for meaningful collaboration. This is a new finding that has not previously been discussed in the literature on forecasting collaboration. It does, in fact, stand in stark contradiction to the assumptions forming the basis of Raghunathan's (1999) and Aviv's (2001; 2002) analytical models. Raghunathan (2001) assumes that retailers can produce completely accurate and reliable forecasts. Aviv (2001; 2002) assumes that combining the retailer's and the supplier's forecasts always improves forecast quality. In light of the research presented in this thesis, these assumptions cannot be considered generally valid.

Secondly, the research provides an explanation why many retailers have less sophisticated forecasting processes than manufacturers. Interviews with leading European grocery retailers indicate that, in general, the retailers can rely on high service levels and high levels of responsiveness from manufacturers, making accurate, medium-term forecasting less critical from their point of view. This observation challenges the assumption that forecasting and collaboration are equally important to manufacturers and retailers and that both parties will benefit from potential improvements. Again, this is a new point of view. Although other studies have suggested that manufacturers probably would benefit more from forecasting collaboration than the retailers (cf. Zhao et al., 2002), this has not been presented as a possible obstacle to collaboration.

Finally, although at this point still a rather tentative finding, it seems that CPFR-style forecasting collaboration may not be a key goal even for the manufacturers. Based on statements made by manufacturers involved in collaboration projects, it seems that many manufacturers have seen the CPFR movement as an opportunity to get access to better demand data and increased retailer commitment to plans, rather than to more accurate forecasts. This is the main reason why they have been quick to embrace CPFR, although the additional benefits of comparing forecasts may be marginal.

Of course, since the observations presented in this thesis are based on a rather limited sample of companies, the generalizability of the observations presented above can be questioned. The fact that an international sample of several leading European grocery retailers has been included in the research does increase the credibility of the conclusions concerning retailer forecasting processes and collaboration interests. However, especially the manufacturer point of view clearly needs to be examined further. It would also be interesting to see in-depth studies of the few existing large-scale implementations of forecasting collaboration to better understand what the actual costs and benefits of these have been and how manufacturers have been able to use the forecast information made available by the retailers. In addition, extending the scope to the US would provide an opportunity to test the validity of some of the conclusions; as lead-times in the US grocery supply chains tend to be longer and inventories higher, retailer interest in and value of forecasting collaboration could potentially be higher. Finally, as the results presented in this thesis are rather industry-specific, expanding the analysis to other sectors would be valuable. In general, identifying successful collaboration practices in any industry and documenting how and why they work would be valuable.

The findings presented in this thesis also give rise to more general questions concerning the impact of the relative power of the players in a supply chain on what supply chain management capabilities they develop. In the European grocery sector it seems that the retailers' significant power has allowed them to outsource a lot of the risk-taking and forecasting to the suppliers. Examining the link between power and capabilities in different industries and supply chains could provide important insights.

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APPENDIX I: PUBLICATIONS

Peer-reviewed articles based on the studies:

- Småros, J., Lehtonen, J-M., Appelqvist, P., Holmström, J. (2003), "The impact of increasing demand visibility on production and inventory control efficiency, *International Journal of Physical Distribution & Logistics Management*, Vol. 33, No. 4, pp. 336-354. (Based on results of Study 1.)
- Lehtonen, J-M, Småros, J., Holmström, J. (2005), "The effect of demand visibility in product introductions", *International Journal of Physical Distribution & Logistics Management*, Vol. 35, No. 2, pp. 101-115. (Based on results of an initial version of Study 2.)
- Småros, J. (2003), "Collaborative Forecasting: A Selection of Practical Approaches", *International Journal of Logistics: Research and Applications*, Vol. 6, No. 4, pp. 245-258. (Based on results of Study 4.)

Conference papers based on the studies:

- Lehtonen, J-M, Småros, J., Holmström, J. (2004), "The effect of demand visibility in product introductions", *16th Annual NOFOMA Conference*, Linköping, Sweden, June 7-8, 2004. (Based on results of an initial version of Study 2.)
- Småros, J. (2004), "The value of point-of-sales data in managing product introductions: Results from a case study", *16th Annual NOFOMA Conference*, Linköping, Sweden, June 7-8, 2004. (Based on results of Study 3.)
- Småros, J. (2002), "Collaborative forecasting in practice", *Logistics Research Network Annual Conference*, Birmingham, UK, September 2002. (Based on results of Study 4)
- Småros, J., Angerer, A., Fernie, J., Toktay, B., Zotteri, G. (2004), "Retailer Views on Forecasting Collaboration", *Logistics Research Network Annual Conference*, Dublin, Ireland, September 9–10, 2004. (Based on results of Study 6.)

APPENDIX II: RESEARCH CO-OPERATION

Three of the studies (Studies 1, 2, and 6) included in this thesis were completed in co-operation with colleagues.

In Study 1, the author worked together with her dissertation advisor Dr. **Jan Holmström** and two simulation experts, Dr. **Juha-Matti Lehtonen** and doctoral student **Patrik Appelqvist**, who were all at the time working at the Helsinki University of Technology. The original idea of the study was the author's. The whole team participated in turning the original idea into a feasible research plan. Jan Holmström was the main responsible for developing the exact specifications for the simulation model. Juha-Matti Lehtonen constructed the simulation model. Jan Holmström performed the simulation runs based on data collected by the author and himself. The author was the main responsible for analyzing the results of the simulations, comparing them to extant literature, and for formulating the conclusions of the study.

Study 2 was conducted in two phases. In the first phase, the author again worked together with Jan Holmström and Juha-Matti Lehtonen. In this phase, the simulation model specifications were produced by the author and Juha-Matti Lehtonen. Juha-Matti Lehtonen created the simulation model and conducted the simulation runs based on data collected by the author. Jan Holmström was the main responsible for developing the bias and delay metrics used in the study. Lehtonen came up with the solution for measuring increase in demand variability for products with rapidly changing demand. Juha-Matti was also the main responsible for producing the initial analyses of the first simulation results. The author's role at this point was to place the results into a wider contextual framework within the literature on demand distortion and information sharing and to formulate the conclusions of the study. In the second phase, the author worked alone and conducted additional simulation runs using different combinations of parameters to better understand how they impact on the results. The author also analyzed the results more extensively and further developed the bias and delay measures to address some of the practical problems related to their use. Finally, the author, based on the new analyses, revised the conclusions of the study.

In Study 6, the author worked together with doctoral student **Alfred Angerer** (University of St. Gallen, Switzerland), professor **John Fernie** (Heriot-Watt University, Scotland), associate professor **Beril Toktay** (INSEAD, France), and associate professor **Giulio Zotteri** (Politecnico di Torino, Italy). The study was led and organized by the author. The author developed the first draft of the interview questionnaire, which was then modified based on feedback from the team. The author also conducted the first test interview. Each of the team members conducted interviews with retailers operating in their region. In addition, each of the members wrote case descriptions of the retailers that they had interviewed and participated in inspecting the documentation produced by the other team members. Data analysis and formulation of conclusions to date has been done by the author. Joint analysis of the data is planned.

APPENDIX III: QUESTIONNAIRE USED IN STUDY 5

1. Collaboration process
    - Describe the new collaboration process
    - How has the collaboration been organized (who does what? how are the responsibilities divided between the retailer and the manufacturer?)

2. Expected and attained benefits
    - What problems did the collaboration originally set out to solve?
    - What is the current focus of the collaboration?
    - Have you tried to assess the potential of reducing these problems (e.g. from a cost or customer service perspective)?
    - What results has the collaboration pilot already produced?
    - What potential additional benefits are you expecting the collaboration to result in?

3. Necessary investments and extra labor related to the collaboration process
    - What amount of labor is related to the collaboration process and how is it divided between the retailer and the manufacturer?
    - How do you expect the labor requirements to develop in the future, e.g. if the process is scaled up to include more products?
    - How has the collaboration impacted on the total amount of labor (Have new tasks been introduced? Have tasks moved from one function or organization to another?)
    - What investments have been made (e.g. in software development)?
    - What investments would a scale-up of the collaboration process require?

4. Future plans
    - What are you plans for the future of this kind of collaboration?
    - How could the collaboration process be improved?

5. Assessment of the collaboration pilot
    - How has the performance of the new collaboration process been measured?

APPENDIX IV: QUESTIONNAIRE USED IN STUDY 6

0. About the retailer

0.01 General information

- brief description of retailer's business and its market position
- market share (%)
- turnover (euros)

0.02 Chains and store formats

- brief description of each chain or store format (competitive position, target customers, assortment etc.)
- number of stores per chain or store format
- store size in square meters per chain or store format
- number of SKUs per chain or store format

0.03 Private label strategy

- private label penetration (% of SKUs or % of sales)
- price positioning of private labels
- relationship with private label manufacturer (e.g. brand manufacturer also selling private label, exclusive contract, joint venture, vertical integration)

1. Supply chain structure and performance

1.01 What are the main distribution alternatives from manufacturers to retail stores:

- describe the main distribution alternatives (direct store delivery, distribution through retail distribution centers, cross-docking terminals etc.) used
- who runs the different parts of the supply chains (distribution centers, terminals etc.)?
- for which product types are the different distribution alternatives used?
- what proportion of total goods handled (measured in volume, euros or order lines) do the different distribution alternatives represent?

1.02 Manufacturers' responsiveness

- what are the order-to-delivery lead times when goods are ordered from manufacturers (either by retailer's stores, distribution centers, or terminals)?
- are there notable differences between the different product types (non-food, packaged goods, fresh goods, greengrocery)?

1.03 Manufacturers' service level performance

- how high are the manufacturers' service levels typically (when delivering to retailer distribution centers, terminals or stores)? Estimate if not measured.
- are there notable differences between the different product types (non-food, packaged goods, fresh goods, greengrocery)?
- is there a notable difference between the normal material flow and situations where demand changes notably, e.g. campaigns or seasons?
- are the service levels sufficiently high?
- do you need to keep additional stock to protect yourself from manufacturer delivery problems?
- what do you think are the main factors causing manufacturer service level problems?

1.04 Distribution centers' stock levels

- how much stock of packaged goods, frozen goods, fresh goods and greengrocery (measured in days of supply) is typically kept in the distribution centers?
- is the inventory turnover sufficiently high?
- what are the main factors causing low inventory turnover?

1.05 Distribution centers' and terminals' responsiveness

- what is the order-to-delivery lead-time (measured in hours or days) when the retail stores order goods from distribution centers or terminals?
- are there notable differences between the different product types (non-food, packaged goods, fresh goods, greengrocery)?

1.06 Distribution centers' and terminals' service level performance

- how high are the distribution centers' or terminals' service levels towards the stores typically? Estimate if not measured.
- are there notable differences between the different product types (non-food, packaged goods, fresh goods, greengrocery)?
- is there a notable difference between the normal material flow and situations where demand changes, e.g. campaigns or seasons?
- are the service levels sufficiently high?
- what are the main factors causing distribution center or terminal service level problems?

1.07 Retail stores' stock levels

- how much stock of non-food, packaged goods, frozen goods, fresh goods and greengrocery (measured in days of supply) do the retail stores typically carry? Estimate if not measured.
- are there notable differences between chains or store formats?
- are the inventory turnovers sufficiently high?
- what are the main factors causing low inventory turnover?

1.08 Delivery frequency to retail stores

- how often (measured in times per week) are non-food, packaged goods, frozen goods, fresh goods and greengrocery delivered to the retail stores?
- are there notable differences between the chains or store formats?

1.09 Shelf availability

- is retail store shelf availability measured? if shelf availability is measured: how and how often is it measured? if it is not measured: why?
- how high is the shelf availability typically for packaged goods, frozen goods, fresh goods and greengrocery? Estimate if not measured.
- are there notable differences between the chains or store formats?
- is there a notable difference between the normal material flow and situations in which demand changes (e.g. campaigns, holidays, or seasons)?
- is the shelf availability high enough?
- what are the main factors causing retail store shelf availability problems?

1.10 The effect of situations in which demand changes significantly (e.g. campaigns, seasons, holidays) on the supply chain:

- do special events (campaigns, product introductions etc.) or circumstances (seasons, holidays, etc.) change the supply chain structure, order-to-delivery lead times or stock-keeping principles in the supply chain?

2. Control and decision making

2.01 Control over assortment decisions

- who makes the assortment decisions (i.e. decides what products are included in a particular assortment)?
- on what level are the assortments formed (individual store, store groups, entire chain)?
- is the assortment formation completely centralized or can the individual stores affect their assortments, to what extent?

2.02 Control over product presentation decisions
- does the retailer use planograms?
- who draws the planograms?
- can the individual stores make product presentation decisions (i.e. deviate from the planograms), to what extent?

2.03 Making assortment and product presentation decisions
- are forecasts of any kind (quantitative or qualitative) used when making assortment decisions (i.e. when deciding what products to include) or product presentation decisions (i.e. when drawing the planograms)?
- how is forecasting done (who forecasts, what forecast method is used, what input data are used, and what is the forecasted time span?)
- on what level does forecasting take place (store, store cluster, chain etc.)?
- what is the forecast accuracy typically? Estimate if not measured.

2.04 Promotional activity in the market
- how many SKUs are typically on promotion per store format and month?
- do you run more or less campaigns than your closest competitors?

2.05 Control over promotional decisions
- who decides on the promotions, promotion types, products and prices?
- on what level are the campaigns run (store, store cluster, chain)?
- can the individual stores make campaign decisions, to what extent?

2.06 Making promotional decisions:
- are forecasts of any sort used when making promotional decisions?
- how is forecasting done (who forecasts, what is the forecast method used, what input data are used, and what is the forecasted time span)?
- on what level does forecasting take place (store, store cluster, chain etc.)?
- what is the forecast accuracy typically? Estimate if not measured.

2.07 Control over price decisions:
- on what level are the price decisions (store, store cluster, chain)?
- can the individual stores make price decisions, to what extent?

2.08 Other relevant decisions
- are there other decisions (e.g. setting of store replenishment parameters) made on the chain or store level that have a significant impact on the flow of goods through the supply chain?

3. Main material flow management processes in the supply chain

3.01 How is the distribution centers' **normal material flow** (i.e. excluding campaigns, strong seasons etc.) managed?
- how are inventory level targets set?
- who is in charge of ordering (either the manual activity or supervising automated ordering)?
- how and using what information is the replenishment order formed?
- are forecasts used when orders are formed?
- how is forecasting done (who forecasts, what is the forecast method used, what input data are used, and what is the time span forecasted)?
- what is the typical forecast accuracy? Estimate if not measured.
- is the forecast accuracy sufficient?
- what are the main factors causing forecast accuracy problems?

3.02 How is the distribution centers' material flow managed in situations where **demand changes significantly** (e.g. campaigns, product introductions, holidays, seasons)?
- are the inventory targets different?
- are the replenishment orders formed in a different way?
- is forecasting done in a different way (who forecasts, what is the forecast method used, what input data are used, and what is the time span forecasted)?
- what is the typical forecast accuracy? Estimate if not measured.
- is the forecast accuracy sufficient?
- what are the main factors causing forecast accuracy problems?

3.03 How is the **normal material flow** (as opposed to in campaign situations, during seasons etc.) through the retail stores managed?
- for which products are automatic ordering, order suggestions or manual ordering used?
- who is in charge of ordering (either manual activity or supervising automated ordering)?
- how are the orders formed when employing automatic ordering?
- how are the orders formed when employing order suggestions?
- how are the orders formed when employing manual ordering?
- are forecasts of any sort used in ordering?
- how is forecasting done (who forecasts, what forecasting method is used, what input data are used)?
- what is the typical forecast accuracy? Estimate if not measured.
- is the forecast accuracy sufficient?

- what are the main factors causing forecast accuracy problems?

Additional questions if automatic or semiautomatic ordering (e.g. order suggestions) is used?

- what system parameters are used?
- how are the parameters set and by whom, how often are they updated?

3.04 How are the material flows through the retail stores managed in situations where **demand changes significantly** (e.g. campaigns, product demonstrations, holidays, seasons)?

- for which products are automatic ordering, order suggestions or manual ordering used?
- are there changes in how the orders are formed (when ordering manually, using order suggestions, and when employing automated ordering)?
- are there changes in how forecasting is done (who forecasts, what forecasting method is used, what input data are used)?
- what is the typical forecast accuracy? Estimate if not measured.
- is the forecast accuracy sufficient?
- what are the main factors causing forecast accuracy problems?

3.05 Overstock

- what happens when a supply chain member (supplier, distributor, retail store) is left with unnecessary stock?
- is the risk of overstocking somehow shared in the supply chain?

3.06 Stock-outs

- what happens if a manufacturer cannot deliver (are there e.g. service level sanctions)?
- does the retailer give the suppliers any store shelf availability guarantees?

3.07 Current material flow management performance and development needs

- what is your opinion of the current performance of material flow management through retail distribution centers, are there development needs?
- what is your opinion of the current performance of material flow management through retail stores, are there development needs?

3.08 Current forecasting performance and development needs

- what is your opinion of the current performance of forecasting at the retail distribution centers, are there development needs?

- what is you opinion of the current performance of forecasting at the chain or store level, are there development needs?

4. Most important improvement opportunities in the area of logistics

4.01 What are the main development opportunities in the area of daily consumer goods logistics?
- in the short term (<= 3 years)
- in the long term (> 3 years)
- are there differences between packaged goods, frozen goods, fresh goods and greengrocery?
- are there differences between the different store formats?
- what are main development opportunities at the different echelons of the supply chain (manufacturer's production and warehousing, distribution, store operations)?

5. Collaboration and information exchange in the supply chain

5.01 Current information sharing practices (i.e. exchange of information beyond the typical price, product information, shipment notices etc.)
- what information do you receive from the suppliers (in connection with product introductions, campaigns, holidays and seasons, in other situations)?
- how is the information used, by whom (job and function)?
- what information do you give to suppliers (in connection with product introductions, campaigns, holidays and seasons, in other situations)?
- how is the information used, by whom (job and function)?

5.02 Current state of collaborative planning
- what kind of collaborative planning do you engage in together with suppliers (in connection with product introductions, campaigns, holidays and seasons, in other situations)?
- how does the planning collaboration happen in practice (what persons are involved (jobs and functions), who does what, how is the final plan formed, how does collaborating improve the quality of the plan)?
- what are the benefits of this type of collaboration to the retailer and to the supplier (operational, financial, organizational etc. benefits)?

5.03 Current state of collaborative forecasting

- what kind of collaborative forecasting do you engage in together with suppliers (in connection with product introductions, campaigns, holidays and seasons, in other situations)?
- how does the forecasting collaboration happen in practice (what persons are involved (jobs and functions), who does what, how is the final plan formed, how does collaborating improve the quality of the forecast)?
- what are the benefits of this type of collaboration to the retailer and to the supplier (operational, financial, organizational etc. benefits)?

5.04 Current state of replenishment collaboration

- are you involved in some kind of replenishment collaboration?
- how does the replenishment collaboration happen in practice?
- how does collaborating support replenishment?
- what are the benefits of this type of collaboration to the retailer and to the supplier (operational, financial, organizational etc. benefits)?

5.05 Is collaboration / information sharing different with private label suppliers?

5.06 Ongoing or ended development projects

- are you currently engaged / have you been engaged projects in which new information sharing practices or collaborative planning, forecasting or replenishment practices have been developed?
- if you have: please describe the projects (what has been done, how, with whom, with what results, involving what persons etc.)
- if you have not: why?
- what is the current status of these development projects (ended, pending, trial, pilot, small scale implementation, large scale implementation)?

5.07 Experiences from development projects and current practice

- in which situations is collaboration (either exchange of information or joint planning or forecasting) most valuable?
- what collaboration practices work best (e.g. information exchange vs. joint planning or forecasting)?
- what collaboration practices do not seem to work?
- what are the most important benefits of collaboration from the retailer's , point of view?
- what are the most important benefits of collaboration from the supplier's , point of view?

- what are the most important challenges or obstacles of collaboration from the retailer's point of view?
- what are the most important challenges or obstacles of collaboration from the supplier's point of view?
- what costs and investments are involved?

5.08 IT systems supporting information exchange or collaboration
- have you facilitated the information exchange or planning and forecasting collaboration with information systems?
- what types of systems have been used?
- have you needed to invest in new systems?
- have the suppliers invested in new systems?
- are you intending to invest in new information systems in a near future to support information exchange or collaboration?
- are you member of some sort of private or public exchange? are you intending to join one?

5.09 Some retailers engage in collaborative planning and forecasting with their suppliers, others do not actively collaborate but do share information (e.g. point-of-sales data), and some do neither – what do you think explains these differences?

5.10 Value of information exchange and collaboration
- do you think retailers can benefit from increased information exchange or planning and forecasting collaboration with suppliers? how (operational, financial, organizational etc. benefits)?
- do you think suppliers can benefit from increased information exchanged or planning and forecasting collaboration with retailers? how?

5.11 The VICS CPFR model
- if you are familiar with the VICS CPFR model, please give us your thoughts on it

5.12 Retailer's vision of the future:
- do you think information exchange and collaborative planning and forecasting will increase or decrease in the future? why? how fast? (in general, and in your case)
- in what situations do you think collaboration is needed?
- do you think the focus should be more on information exchange or collaboration? why?